Models for Quantifying Safety Benefit of Winter Road Maintenance

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

In countries with severe winters such like Canada, winter road maintenance (WRM) operations, such as plowing, salting and sanding, play an indispensible role in maintaining good road surface conditions and keeping roads safe. WRM is, however, also costly, both monetarily and environmentally. The substantial direct and indirect costs associated with WRM have stimulated significant interest in quantifying the safety and mobility benefits of winter road maintenance, such that systematic cost-benefit assessment can be performed. A number of studies have been initiated in the past decade to identify the links between winter road safety and factors related to weather, road, and maintenance operations. However, most of these studies have focused on the effects of adverse weather on road safety. Limited efforts have been devoted to the problem of quantifying the safety benefits of winter road maintenance under specific road weather conditions. Moreover, the joint effects of and complex interactions between road driving conditions, traffic and maintenance and their impact on traffic safety have rarely been studied.

This research aims to determine the effect of WRM on road safety during snow storm events and develop models that can be used to quantify the safety benefit of alternative winter road maintenance policies, strategies and practices. Two integral aspects of collision risk were investigated, namely, collision frequency and severity. Collision frequency models were developed using winter storm collision data compiled for six winter seasons (2000 to 2006) for a total of 31 highway routes across Ontario. A comprehensive measure, namely, road surface condition index (RSI), was proposed to represent the road surface conditions during a variety of snow events. RSI was used as a surrogate measure to capture the effects of WRM. Other factors related to weather, traffic and road features were also accounted for in the analysis. Problems associated with data aggregation were also investigated. For this purpose, two different datasets were formed, namely, event-based data (EBD) which aggregates data by snow storm events and hourly based data (HBD) which includes hourly records of collision counts and other related factors. These two data sets of different aggregation levels were then used to investigate the effects of data aggregation and correlation (within – event) as well as to develop models for different purposes of benefit analyses. For EBD, Negative Binomial models and Generalized Negative Binomial models were calibrated whereas for HBD, Generalized Negative Binomial models and multilevel Poisson Lognormal models were calibrated. Generalized Negative Binomial models were found to best fit the data for both datasets. It was found that addition

of site specific variables improves model fit. RSI and exposure were found significant for all the models and datasets. Weather factors such as visibility, wind speed, precipitation, and air temperature were also found to have statistically significant effects on collision frequency. All the models were consistent in terms of effects of different variables. The EBD models are useful to quantify the effect of different maintenance service standards and policies with limited information on the details of the weather events and traffic. On the other hand, HBD models have a higher level of reliability capable of providing more accurate estimates on road accidents. As a result, they are useful for determining the effects of different treatment operations. Several examples were employed to demonstrate the application of the developed models, such as quantifying the benefits of alternative maintenance operations and evaluating the effects of different service standards using safety as a performance measure.

To enable a comprehensive risk analysis, collisions under both all-weather conditions and snow storm conditions over the six winter seasons were analyzed to identify the relationship between collision severity and various factors related to road weather and surface conditions, road characteristics, traffic, and vehicles etc., on collision severity. A multilevel modeling framework was introduced to capture the inherent hierarchy between collisions, vehicles and persons involved within the collision data. For each collision data set, three alternative severity models, namely, multinomial models, ordered logit models and binary logit models, were calibrated and compared. It was found that multilevel multinomial logit models were best fit to the data. Moreover issues related to different levels of aggregation were also discussed and results from occupant based data were found to be more reasonable and in line with general literature. Different individual, vehicle, environment and accident location factors were found to have a statistically significant effect on the injury severity levels. Contributing factors at the individual and vehicle levels include driver condition, driver sex, driver age, position in vehicle, use of safety device such as seat belt, vehicle type, vehicle age and vehicle condition. Roadway and environment factors include number of lanes, speed limit, road alignment, RSI/road surface condition, wind speed, and visibility. Other factors include light, and traffic volume. Two case studies were conducted to demonstrate the application of the developed models in conjunction with the accident frequency models for cost benefit analysis.

This research was the first to investigate the direct link between road surface conditions and collisions at an operational level. It has been shown that the developed models are capable of evaluating alternative winter road maintenance policies and operations and assessing the safety benefit of a particular winter road maintenance strategy or decision. This research is also the first to conduct an in-depth analysis on the problem of winter road safety at a disaggregate level that captures detailed temporal variation (e.g., hourly and by storm event)) within small spatial aggregation units (road sections corresponding to actual patrol routes). The safety models developed from this research could be easily incorporated into a decision support tool for conducting what-if analysis of alternative winter road maintenance policies and methods. Moreover these models could provide a mechanism to estimate road safety level based on road surface as well as weather and traffic conditions and therefore could potentially be used for generating safety related information for travelers as part of a winter traffic management scheme. Directions for future work are also provided at the end of this document.

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Dedication

I would like to dedicate this thesis to the memories of my late father, my mother, my wife and my two daughters – Saba Khan and Manha Khan.

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List of Acronyms

Acronym	Definition
AIC	Akaike Information Criterion
AWCD	All Weather Collision Data
BLM	Binary Logit Models
BPR	Bare pavement recovery
CR	Central region
GEE	Generalized estimating equations
EBD	Event-based dataset
EC	Environment Canada
ER	Eastern region
FH	First hour
GEE	Generalized estimating equations
GLM	Generalized linear models
GNB	Generalized Negative Binomial model
HBD	Hourly based data
ICC	Intra-class correlation
LOS	Level of Service
MBL	Multilevel sequential binary logistic model
ML	Maximum Likelihood
MLM	Multinomial Logit Models
MML	Multilevel multinomial logit model
MOL	Multilevel ordered logit model
MTO	Ministry of Transportation, Ontario
MVKm	Million vehicle kilometres
NB	Negative binomial model
NER	North-East region
NI	No Injury
NWR	North-West region
OLM	Ordered Logit Models

OPP	Ontario Provincial Police
PDCS	Permanent data count stations
PLN	Poisson Lognormal Models
RCWIS	Road condition weather information system
RSC	Road surface condition
RSI	Road surface condition index
RT	Road type
RWIS	Road weather information system
SECD	Snow storm event collision data
SH	Second hour
SSD	Stopping sight distance
SWR	South-West region
WRM	Winter Road Maintenance
ZINB	Zero inflated Negative Binomial
ZIP	Zero inflated Poisson

Chapter 1
INTRODUCTION

1.1 Background

Road safety is an important issue to mankind in all its forms. Road safety is normally measured in terms of the number of traffic collisions (or collision rate - expressed in collisions / million vehicle kilometres) that occur on a road network or at particular locations within it (note: accidents, collisions and crashes are used interchangeably in this research). According to a World Health Organization report published in 2004, about 1.2 million people are killed and as many as 50 million injured on the roads around the world each year making it the ninth most major cause of injuries worldwide. Continuation of this trend will lead road accidents to become the third most major cause of injuries worldwide by the year 2020 (WHO, 2004). The cost of these accidents to the society is enormous (Elvik 2000). In Canada accident cost constitutes around 2% of the gross domestic product (Transport Canada 2008).

Winter road safety is of particular concern because driving conditions in winter vary dramatically and deteriorate quickly due to snowfall and ice formation. This can cause a significant reduction in pavement friction and increases the risk of accidents (Brown and Baass 1997; Pisano 2004). Nilsson and Obrenovic (1998) found that drivers are twice more likely to be involved in an accident in winter than in summer for a given distance of travel. Andrew and Bared (1998) estimated that weather related crashes account for as much as 30% and 35% of total reported accidents for the UK and the USA, respectively. Based on crash data from 1995 to 2001, Goodwin (2002) found that 22% of crashes were weather related, of which 32% were due to slick pavement conditions only and 67% were due to the combination of slick pavement and bad weather. A European study (HASTE 2002) found an increase in accident frequency of approximately 9 times for snowy and 20 times for icy road conditions compared to dry surfaces. Maze et al (2006) found that on average inclement weather occurs 25% of a year. Velavan (2006) found a 48% increase in injury related accidents under snowy conditions compared to clear weather conditions. Qiu and Nixon (2008) found an increase of 84 % in the crash rate, 75% in the injury rate and 9% in the fatality rate due to snow precipitation. FHWA

(2010) estimated that 24% of crashes are weather related, resulting in about 7,400 fatalities and over 673,000 injuries. Dodet and Giloppé (2010) found an increase ranging from 1 to 4.8% due to snow covered or icy road surface conditions whereas Pöllänen (2010) found this figure to range between 400% and 500%. Moreover weather severity not only increases the risks at accident prone locations, but can also lead to other locations becoming critical (see for instance Shankar et al 1995).

Each year in Canada, approximately 100,000 traffic accidents occur during inclement weather conditions such as rain, snow, freezing rain and high winds (Andrey and Knapper 2003). According to the Ontario Road Safety Annual Report (MTO, 2007), 9.66% and 11.14% of accidents occurred during rainfall and snowfall respectively in Ontario in the year 2007. These figures were 17.6% and 16.7% for wet and snowy road surface conditions, respectively. Weather related crash costs including both injury and property damage crashes are estimated to be in the range of $ 1 billion per year in Canada (Andrey et al 2001). Litwin and Turrittin (2004) showed that the total accident cost in the province of Ontario was $567.1 million ($125.4 million in direct costs and $441.7 million in indirect costs) for the year 1996. A report by Transport Canada (2007) estimated accident related costs in Ontario to be $18 billion for the year 2004.

One of the remedies to mitigate the negative safety impact of winter weather is to implement effective winter road maintenance (WRM) operations, such as plowing, salting and sanding. These practices help to keep roads clear of excessive snow and ice build-up. Effective WRM can ensure road safety by ensuring road surface conditions remain as similar as possible to bare pavement conditions. Norrman et al (2000) have shown that maintenance activities have reduced accident risks for sites that initially were at high risk. Fu et al (2006) have shown that maintenance operations including anti-icing, pre-wet salting with plowing and sanding have a statistically significant effect on reducing the frequency of accidents.

While essential for keeping roads safe, WRM operations also incur significant monetary costs and negative environmental effects. For example, the direct cost of winter maintenance programs in Ontario is estimated to exceed $100 million annually (Perchanok et al, 1991). This represents 50% of its total annual highway maintenance budget (Buchanan and Gwartz 2005). The total WRM cost is estimated to be $1 billion in Canada, and over $2 billion in the U.S (Transport Association of Canada 2003; National Research Council 2004). These estimates do not include significant indirect costs such as the damage caused to the environment, road side infrastructure, and vehicles due to salt use (Perchanok et al 1991; Environment Canada 2002). A recent study by Environment Canada has concluded that road salts at high levels of concentration pose a risk to plants, animals and the aquatic environment (Transport Canada, 2001). A Risk Management Strategy for Road Salts was subsequently developed to provide measures to manage the risks associated with road salts (RMSRS, 2003).

In summary, both road accidents and WRM operations have huge financial implications. While vital and beneficial in terms of road safety, WRM operations also have side effects. This means that any decisions concerning WRM must take into account their benefit and cost implications. This raises the following questions: What should be the best maintenance policy for a jurisdiction? What is the optimal amount of maintenance operations? Is the introduction of new maintenance technologies cost-effective? What are the road safety benefits? These questions can be addressed only after the quantitative relationship between road safety and WRM is established.

1.2 Winter Road Maintenance (WRM) Management

WRM stands for all those operations, methods and procedures that are applied to restore deteriorated road surface conditions of a roadway or highway network to some specified level of service. Management of WRM involves many levels of decision making ranging from strategic or tactical decisions, such as what level of service policy to use; where to locate depots; and what fleet to use for operational decisions such as when to start plough and salt and how much salt to apply. While varying in scope and complexity, all decisions have cost and benefit implications.

In general, maintenance management and operations in a jurisdiction are guided by a set of standards that specify the minimum level of service to be maintained for the different classes of highways. For example, Ministry of Transportation Ontario (MTO) categorizes highways into five classes based on winter average daily traffic volume (WADT), each having a specific set of maintenance standards defined based on bare pavement status, bare pavement recovery time and snow depth. Other performance measures such as friction and snow coverage have also been used by some other organizations and countries. For example, some Scandinavian countries (Finland, Norway and

Sweden) have introduced friction as a performance measure in their maintenance operations (Transportation Association of Canada, 2008).

Regardless of the performance measures used, all standards involve some level of service designations and threshold values. Decisions on these thresholds values for individual highway classes have significant implications in terms of overall maintenance costs and performance of the highway system. Currently these decisions are mostly made on the basis of judgement and ad-hoc experience. Service class standards for Ontario are given in Table A – 2 to A – 5 in Appendix – A.

There is also significant variation in terms of how a service standard is achieved, as there are usually quite a few choices available for road maintenance operations. In Ontario, e.g. the main methods used in maintenance operations are plowing and salting. A road is plowed when snow accumulation on its surface reaches the maximum allowable depth (2.5cm). Salting is often applied before snowfall or after the road is plowed to melt snow/ice and provide additional traction. When salts are applied in advance of a snow storm, mostly in a liquid form, the operation is considered to be a new technique called anti-icing with the aim of preventing the bonding of snow and ice to the pavement surface. Sanding is mostly used to increase pavement traction when the temperature drops below -12 ^{0}C, under which regular salts are no longer effective (Smith and Zogg 1998; MTO 2004). Decisions on what maintenance operations to use and the treatment quantities should ideally be made on the basis of the cost effectiveness of individual operations, taking into account both safety and mobility benefits.

Furthermore, WRM authorities are increasingly making use of advanced sensor and communication technologies such as road weather information systems (RWIS) in their maintenance decision process. With real-time information from RWIS, managers can make decisions that are more effective on what treatments to use and when to start the treatment operations. Also, with this information, anti-icing strategies could be more effectively implemented (Bourdon 2001; Transportation Association of Canada 2008). However, while some limited studies have shown the potential benefit of RWIS (Strong and Shi 2008), the exact effectiveness of these technologies in terms of safety and mobility improvement is still unknown.

In summary, from the literature, one can note that decision making at all levels of maintenance management relies on the ability to determine the potential safety and mobility benefits that can be achieved through winter maintenance services and the costs associated to the services.

1.3 Safety Effects of Winter Weather and Road Maintenance

Research in the area of winter road safety is mostly focused on effects of adverse weather on road safety (Andreescu and Frost 1998; Knapp et al 2000; Andrey et al 2001; Andrey et al 2003; Andrey and Knapper 2003; Handman 2002, Kumar and Wang 2006). Limited efforts have been devoted to the problem of quantifying the safety benefit of WRM under various weather conditions. In general, two approaches have been used to address this issue. The first approach attempts to develop a direct estimate on the cost-benefit ratio of WRM operations. For example, Thornes (2002) estimated that in the U.K. average benefit-cost ratio of winter road maintenance is 8 whereas in U.S.A. the benefit-cost ratio ranges from 2:1 to 18:1. Similar results have obtained by Hayashiyama et al (2001), suggesting a benefit-cost ratio of between 5.7 and 11.1. Kirikoshi et al. (2010) analysed a 1.7 Km long section of Highway 4, in Aomori, Japan and calculated the B/C ratio of snow removal based on travel time alone to be 1.23. These results are useful in proving a general estimate on the benefit of winter road maintenance, but are insufficient for assessing specific maintenance policies and decisions as the corresponding cost-benefit ratios could vary in a wide range.

The second approach is to compare the difference in accident frequency between conditions with different levels and types of winter road maintenance and without maintenance. Hanbali (1992) conducted a study on the effectiveness of salting on 570 miles of road (520 miles of two lane undivided freeways and 50 miles of divided freeways) randomly selected from New York, Minnesota, and Wisconsin. Hourly traffic flows and accident data were obtained from these areas for 1990 and accident rates over the periods before and after salting were estimated and compared. The main findings of the research are summarized below:

- For divided highways, salting was found to have a significant effect on safety within two hours after salting whereas for undivided highways the effective period was 4 hours.

- The average reduction in accident rate was 87% and 78% for two-lane undivided highways and freeways, respectively.
- During the first four hours following the application of salt during a winter storm, the direct road user benefits was $6.50 for every $1.00 spent on maintenance operations for two lane roads. During the first two hours following the application of salt during a winter storm, the direct road user benefit was $3.50 for every $1.00 spent on maintenance operations for freeway roads.

Note that in this study, the direct road user benefits were measured using travel time and operating cost savings alone. One of the implicit assumptions made in this study was that all reductions in accident rates were solely attributed to maintenance operations, which seems to be a major shortcoming.

Norrman et al (2000) was among the first who attempted to quantify the relationship between road safety and road surface conditions. In their study, they classified road surface conditions into ten different types based on slipperiness and compared the crash rates associated with the different road surface types using winter weather and collision data from two stations within a radius of twenty five kilometres from two RWIS stations in the county of Halland, Sweden for the periods from 1991 to 1996. Precipitation, temperature, relative humidity and wind were considered as part of the weather elements. Accident distribution for each slipperiness type and the corresponding risk was developed. These values were then compared to maintenance activities using a ratio defined as “the number of times maintenance is done at the time of a traffic accident” divided by “the total number of traffic accidents on that type of slipperiness”.

The approach taken by the Norrman et al (2000) study has several limitations. First of all, it is an aggregate analysis in nature, considering roads of all classes and locations together. The aggregate approach may average out some important environmental and operating factors that affect road safety at a local level and therefore the results may not be applicable for assessing decisions at an operational level with an analysis scale of a maintenance yard. Secondly, the simple categorical method of determining crash rates may introduce significant biases if confounding factors exist, which is likely the case for a system as complex as highway traffic. Furthermore, the procedure cannot be used to compare the effect of different maintenance operations.

Fu et al (2006) investigated the relationship between road safety and various weather and maintenance factors, including air temperature, total precipitation, and type and amount of maintenance operations. Two sections of highway 401 were considered. They used a Generalized Linear regression Model (Poisson distribution) for analyzing the effects of different factors on safety. They concluded that anti-icing, pre-wet salting with plowing and sanding have statistically significant effects on reducing the number of accidents. Both temperature and precipitation were found to have significant effects on the number of crashes. This study also suffers from several limitations. First, the data used in their study was aggregated on a daily basis, assuming uniform road weather conditions over time of day for each day. Secondly, their study could not account for some important factors due to data problems, such as traffic exposure and road surface conditions. Furthermore, the data available for their analysis covered only 9 winter months and thus the power of the resulting model needs to be further validated. One of the implications of these limitations is that their results are not directly applicable for quantifying the mobility benefit of WRM of other highways or maintenance routes.

Nordic countries have conducted extensive research on issues related to winter road safety and road maintenance (Wallman et al, 1997). However, the sources of the original studies are difficult to trace as they were written in other languages in the form of research reports instead of peer reviewed publications. In terms of research methodology, most of these studies relied on simple comparative analyses instead of rigorous statistical modeling. Nevertheless, the findings were in general consistent, showing that winter weather increases the risk of accidents by virtue of poor road surface conditions and that maintenance lowers crash risk by improving road surface conditions.

1.4 Issues with Existing Methodologies

As described in the previous section, a number of past studies have been dedicated to the issue of winter road safety. However, most of these studies have focused either on the effect of weather only or suffered some methodological issues, with the following specific limitations:

- ❖ Most research relied on data that were either incomplete or aggregated. For example, many studies have used aggregated seasonal and yearly average for weather and traffic conditions because daily and hourly weather and traffic counts were not available. Also, road condition data and accident reports obtained from different organizations were not consistent with each other.

- ❖ Most investigations cover large regions with large spatial (e.g. cities, provinces) and temporal (e.g. daily, seasonal, annual) analysis units. Such macro-level analysis cannot take into account local variations in weather and road conditions, traffic and maintenance operations.
- ❖ Very little empirical evidence exists in literature regarding the effects of winter road maintenance treatments on road safety, mostly, due to the fact that detailed maintenance records were not available.
- ❖ Most findings and results reported in literature were obtained directly from observations with naive before-after analysis with few resulting from systematic statistical analysis.

The aggregate approaches employed by researchers can have many problems associated with them (see for instance Mensah and Hauer 1998). To cope with these problems, this research proposed a disaggregate methodology to investigate the relationship between winter road safety and WRM. Patrol route (road section maintained by a single contractor for maintenance purpose) is used as the spatial level of analysis and snow storm event or hourly observations (within the snow storm event) as the temporal unit of analysis.

1.5 Research Objectives

As discussed previously, the effect of winter weather on road safety has been studied extensively by many researchers; however, few past efforts have investigated the link between the road safety and the amount of WRM applied on the road during a specific snow storm. The current understanding of the relationship between road safety and WRM has not reached a level that is sufficient for evaluating the cost-effectiveness of alternative winter maintenance polices and operations. This research is aimed at addressing this knowledge gap with the following specific objectives:

1. Investigate the relationship between winter road safety and contributing factors associated to road accidents under adverse winter weather conditions;

2. Develop statistical models for collision frequency that relate winter road safety to WRM through road surface conditions measures as well as exposure and other environmental factors at a disaggregate level (snow storm events or the hours within);
3. Develop disaggregate statistical models for injury severity using winter season and snow storm event data. The developed models will be used in conjunction with the collision frequency models for benefit – cost analysis;
4. Develop a methodology that can be applied to assess the safety benefit of alternative maintenance policies, operations strategies and decision, and demonstrate the application of this methodology through examples.

1.6 Organization of Thesis Proposal

This thesis consists of seven chapters. Chapter 1 was introduction to the problem. The remaining thesis is organized as follows:

In chapter 2, a literature review is presented in the area of winter road safety: effects of weather, traffic and maintenance on safety, collision frequency and injury severity models.

Chapter 3 describes the proposed methodology, sites and data used for the analysis and data processing.

Chapter 4 describes the development of disaggregate collision frequency models and their application.

Chapter 5 describes the development of disaggregate injury severity and effects of different variables on injury severity.

Chapter 6 highlights the conclusions and main contributions of this research.

Chapter 2
LITERATURE REVIEW

Winter road safety has been studied from different perspectives by many researchers, including exploratory analysis of factors affecting winter road safety, examination of the link between winter road maintenance, road surface conditions and safety, and comparison of different modeling approaches.

This chapter provides a detailed review on all these topics in six parts. In the first section, previous research on general factors affecting road safety is presented. In the second part, past studies on the effects of winter maintenance and road surface conditions on safety are synthesized. In the third part, literature related to collision frequency models is reviewed. Fourth part presents literature related to collision severity models. In the fifth part different measures for model assessment and testing are discussed. Finally, the sixth part discusses relevant literature regarding issues related to data aggregation and correlation.

2.1 Conceptual Framework: Factors Affecting Winter Road Safety

There are a large number of factors influencing the road safety (crash occurrence and its consequences) of a highway under winter conditions (Ostrom and Eriksson 1993; Miaou and Lum 1993; Andrew and Bared 1998; Handman 2002; Miaou et al 2003; Shankar et al 1995; Fridstrøm 1995; Kopelias et al, 2007). The major factors affecting winter road safety can be grouped into three categories, namely, weather characteristics, traffic conditions (flows, operating speeds, density), and maintenance operations, as schematically illustrated in **Figure 2-1**. The following section provides a detailed description on these factors and the related research.

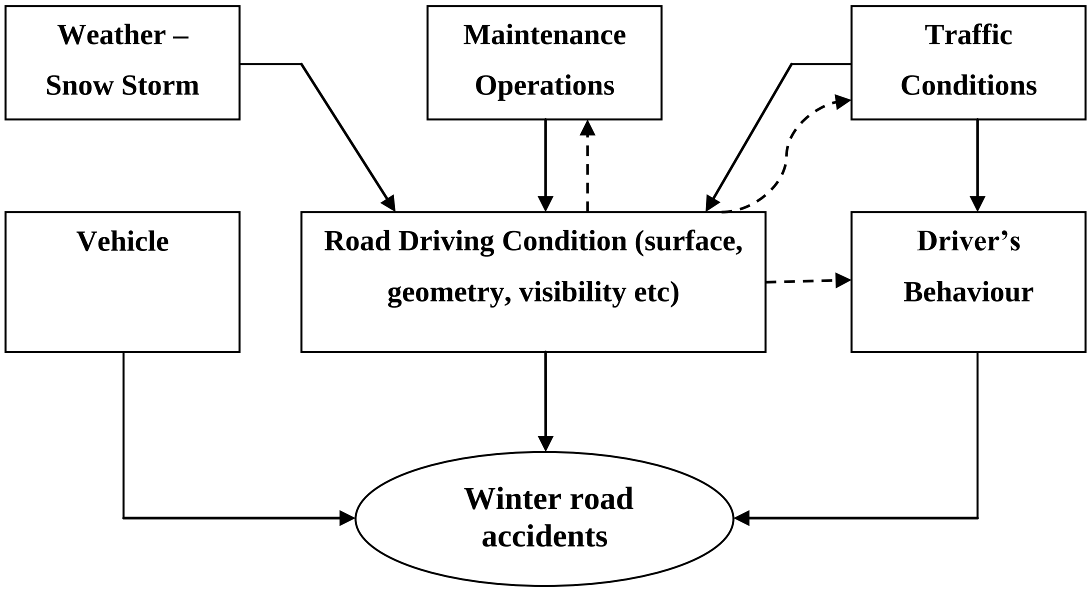

Figure 2-1: Relation between maintenance, weather, traffic and safety

2.1.1 Weather Effect on Safety

Adverse weather such as snow storms and freezing rains is the main cause of poor road surface conditions and thus road accidents. Weather related factors that have an effect on road safety include freezing precipitation, frozen precipitation, liquid precipitation, severe and major storms, temperature, visibility, and wind speed (Edwards 1998; Feng 2001; US Department of commerce 2002; Strong et al 2010). In addition to the literature reviewed for weather effects on road safety in this section (mostly related to effects of weather on collision frequency), additional references are provided in Appendix G.

Andreescu and Frost (1998) analyzed the correlation between daily accidents with weather variables (temperature, rain fall, and snowfall) using three years of weather and collision data (1990 -1992) from the Island of Montreal, Quebec. To remove variation in the number of accidents per day, the average number of accidents was calculated for each day of the week using the entire three years of data. Then, differences from the appropriate mean were determined for each individual day. This difference was then used as the number of accidents in their subsequent modeling process. Linear regression equations were developed for each year to relate daily accident frequency and individual independent variables. They observed that the number of accidents increased with increase in snowfall or rainfall intensity. The increase was however more in case of snowfall than rainfall. Temperature was not found significant.

Note that their use of simple linear regression models for the relationship between accidents and the dependent variables makes the results less reliable. For example, for the year 1990, their regression model shows that the number of accidents is a positive function of rainfall intensity whereas the related plot shows a high number of accidents at low values of rainfall. Moreover they did not account for traffic exposure.

Later, Knapp et al (2000) studied the impacts of winter storms on crash frequency and traffic volume reduction. Hourly data for accidents, traffic volume and weather was collected in Iowa for a 48 km long segment of interstate highway from 1995 to 1998 and fifty four winter storms were identified based on freezing temperature, precipitation and non-dry pavement surface. The following Poisson regression model was calibrated:

$$\ln(\mu) = -2.135 + 0.0682\,E + 0.156\,ED + 0.494\,SI + 0.009\,MGW \qquad \textbf{(2 – 1)}$$

where

μ = Mean number of accidents in a storm;

E = Exposure in million vehicle kilometres;

ED = Event Duration in hours;

SI = Snowfall intensity in centimetres per hour; and

MGW = Maximum gust wind in kilometre per hour.

As seen in **Equation 2-1**, crash frequency increases with exposure (vehicles million kilometres), snow storm duration, snowfall intensity and maximum wind gust speed. Maximum wind gust speed was however not significant. It should be noted that they limited their analysis to those snow storms with at least four hours of duration and intensity greater than 0.51 cm/hour. They only tried standard Poisson regression model. It is not clear whether there is any evidence of over-dispersion in their accident data. They also found that the difference in crash rates between snow storm and non-snow storm is about 1300%. One reason for getting this high number could be the reduction in traffic volume within snow storms thus increasing the crash rate within snow storms.

Khattak and Knapp (2001) applied match pair technique for quantifying the effects of winter snow storms on accident severities. Winter storms were defined based on the definition in Knapp et al (2000) and the same dataset and location was used for the analysis. If a storm occurred on Monday in a January from 2PM to 6PM then all Mondays in the month of January for the same duration were treated as non-storm events. The comparison showed that crash rates (injury and non-injury) increased significantly in snow storm event period compared to non-event period. Logit model was developed for the injury severity level. Weekends and high wind speed, curved road sections were found to increase the probability of injury crashes whereas increase in traffic volume, straight road sections and single vehicle accidents were found to cause a reduction in the probability of injury crashes.

Andrey et al (2003) analyzed accident and precipitation data of six Canadian cities, including Halifax-Dartmouth, Ottawa, Québec, Hamilton, Waterloo Region, and Regina, from 1995 to 1998. They aggregated the data by intervals of six hours and employed pair matching technique to compare accidents on periods of days under adverse weather conditions with accidents on time periods of similar days but with normal weather conditions. For each matching pair, they computed accident risk by dividing the number of accidents on stormy days over those on non-stormy days for different scenarios. They found that the overall collisions frequency and injury severity collisions due to precipitation increased by 75% and 45%, respectively. Moreover, snowfall effects were more pronounced than rainfall for collision; however, the resulting accidents are less severe in nature. Similar results were reported by HASTE (2002) and Velavan (2006) where the former reported an increase in accident frequency of about 9 times for snowy and 20 times for icy road compared to dry surface whereas the later reported 48% increase in injury related accidents under snowy conditions compare to clear weather.

According to Andrey and Knapper (2003) the risk associated with rainfalls are mainly due to visibility, since collision rates quickly return to near normal after the rain stopped. This is true even if roads continue to be wet. In the case of snowfalls, accident risks usually remains elevated for an extended period. It was also found that high winds and fog are responsible for a small proportion of crashes.

In a more recent study, Andrey (2010) extended their work to 10 Canadian cities using data collected from 1984 to 2002 to investigate the effects of weather on crash severities in the long run. Severity levels considered are fatalities, minimal, minor or major injuries. Match pair technique was utilized with control one week apart from the event. Andrey (2010) concluded that the risk of minimal or minor injury crash increases by 74% due to rain fall and 89% due snowfall whereas for major injury and fatal crashes the risk increases by 46% and 52% under rain fall and snowfall conditions, respectively.

Eisenberg (2004) developed a set of state-level collision models using 25 years (1975-2000) of data about weather, traffic and accidents from USA (48 states for fatal and 17 states for non-fatal and total). Both monthly and daily models were developed using Negative Binomial (NB) distribution. Exposure was used as annual vehicle miles travelled. Monthly model shows a reduction in fatalities with snow precipitation and increase in non-fatal accidents. The effects are positive for total crashes. In case of the daily models these effects were positive for all severity levels and total accidents. Daily models were reanalysed using dummy variables for snow precipitation and it was found that only heavy precipitation increases fatalities. Others effects remain the same. For the total accidents the effects were more pronounced when snow precipitation was in the medium range exhibiting a bell shape relationship.

In an attempt to find the effect of snowfalls on crash rate, Eisenberg and Warner (2005) conducted research on relationship between crash and weather based on data obtained for the period 1975-2000 for 48 states in the US. They defined the time periods into dry, rainy (with some precipitation and no more than 0.5 cm of snowfall), and snowy (with at least 0.5 cm of snowfall). NB models were calibrated with number of crashes as the dependent variable and precipitation, fixed effects (dummy variables) representing the effect of geographical differences (at the state level), month, year, and traffic exposure (in million vehicle miles traveled per year). Incident rate ratios (IRR), defined as the ratio of accident rate over a period of particular condition divided by accident rate under dry periods, were computed. The accident rates were computed for rainy days, first snowy days and non-first snowy days, for three types of crashes, namely, fatal, injury and property damage, and compared to those in dry days. Based on the estimated IRR they showed that during snowfalls, the number of non-fatal injury and property damage crash rates increased but fatal crash rate decreased compared to dry seasons. This finding is consistent with those from other researchers (e.g. Brown and Baass 1997;

Andrey et al 2003; Strong et al 2010). One plausible explanation of this pattern could be slowing down of vehicles under such conditions (Knapp et al., 2000).

Eisenberg and Warner (2005) also found that first snowy days were more dangerous in terms of fatalities than non-first snowy days. Maze and Hans (2007) also found similar results by concluding that accident risk is about 3.5 times higher at the start of a winter season than at the end. They attributed this to drivers' lack of memory over the summer season for this cause.

Sherif (2005) tried to establish a link between road surface temperature (RST), surface moisture and safety. For this purpose data for one winter season from November 01, 2001 to March 31, 2002 was collected from the city of Ottawa, Ontario, Canada. Traffic exposure was however not considered which was taken care of by limiting the data to specific conditions to yield a more uniform data set. Sherif (2005) limited the data to weekdays only where each day was considered from 6:00 AM to 9:00 PM. Moreover this data was further divided into two sets: peak period (6:00 AM to 9:00 AM and 3:00 PM to 6:00 PM) and off peak period. Lastly, all the data that was collected outside the temperature range of -8 to +8 C was dropped from the analysis. Data was further divided into dry pavement and wet pavement data. Three levels of severity for collisions, namely, fatal, injury and property damage and three impact types, namely, rear end, single vehicle and other were considered for the analysis.

Two different approaches were employed for the severity levels and impact types defined above. This was done for each degree of temperature from -8 to +8 C. The first was to come up with pavement moisture risk factor (PMRF) defined as the ratio of collision rate on wet surface to collision rate on dry surface. A value greater than 1 (one) indicated high collision risk for wet surface and vice versa. In general accident risk was high on wet surfaces. The second was an empirical Bayesian technique. In this case the total collision rate ($\bar{\theta}$) was considered as the prior information and the collision rate for a subgroup (θ_i) was incorporated to get the posterior information. Collision rate was defined as ratio of the number of collisions to the corresponding number of hours. Situation was hazardous when P($\theta_i > \bar{\theta}$) > δ, where δ is some predefined level such as 95%. Their results showed those wet surfaces were found hazardous when temperature ranges from +1 to -2 C.

This research has several limitations. First, data is aggregated at a very high level (city of Ottawa) which may have masked variation within different types of highways, both accident wise and weather wise. Secondly, wet surfaces can range from wet to icy, each with a different impact level, which were however, considered to be equal in terms of their effect on safety. Again no accidents occurring on dry surface will lead to an infinite PMRF value. Finally, the research made use of only one season of data, which is not sufficient to capture the large spatial - temporal trends.

Hermans et al (2006a) conducted a research on the effect of weather factors on road safety. Seventeen factors related to wind, temperature, precipitation and visibility were considered. Data were collected from 41 stations in Netherlands in 2002, including hourly data on cloudiness, precipitation duration, precipitation amount, relative humidity, presence of precipitation, presence of fog, presence of snow, presence of thunderstorm, presence of black ice, presence of hail, and horizontal visibility. These authors found that some factors were significant at some sites but not significant at others. Some of the significant factors had positive coefficients at some sites and negative otherwise, indicating opposite impacts on safety. They tried four types of models, including Poisson, zero inflated Poisson, negative binomial, and zero inflated negative binomial model. Negative binomial model was found to give the best results. For the effect of precipitation, they concluded that duration of precipitation is more significant than amount of precipitation. Presence of light reduced accidents whereas precipitation and wind gust speed were found to increase accidents. While the exact reasons for these mixed results were unknown, the possible causes could be inappropriate model structure, cofounding of missing factors and large geographical (coastal areas vs. inter cities) and temporal (different seasons) variations. Nevertheless, this research did discuss the challenges of modeling weather effect on road safety.

Hermans et al (2006b) analysed the monthly frequency and severity of accident based on monthly data collected from 1974 to 1999 from Belgium using state space approach. Weather variables considered in the analysis were precipitation, sun light hours and percent of days with sunlight, freezing temperature, precipitation, snow and thunderstorm. Two severity levels were considered, fatal or major injury and minor injury. Percent days with thunderstorm and precipitation were significant only with minor injuries with a positive effect. Sun light hours and days with precipitation were found to increase both minor injury and major injury or fatal collision risk. Percent of days with freezing temperature was found to decrease both minor injury and major injury or fatal collision risk.

Again the analysis was conducted at a very aggregate level and therefore the variables might not represent the true conditions at the time of accidents.

Qin et al (2006) analysed accident and snow storm data from two winter seasons 2000-01 and 2001-02 from Wisconsin, USA. Temporal effects of the storms were calculated as $RT_i = (T_i - T_{ss})/(T_{se} - T_{ss})$ where RT_i is the relative crash time of crash i as a measure of crash risk; T_i is the crash time of crash i; T_{ss} is the snowstorm starting time; and T_{se} is the snowstorm ending time. It was found that crash risk was high for all highways at the start of storms and subsequently dropped in the later periods. However, the drop was more rapid for state maintained roads than for local roads. This may be due to higher maintenance standards for state maintained roads than for local roads. Similar results were obtained by Bergström (2006). NB model was used for the relation between crash counts and other variables. Results showed that the number of freezing rains, storm duration, wind speed and salt per lane mile were associated with high collision rates whereas crew out time before the storm and de-icing hours were associated with low collision rates. Positive effects of salt can be explained by the need of more salting during harsh events.

One of the major limitations of this study is the absence of traffic data which is usually a major predictor of accidents. Moreover the analysis was performed on a highly aggregated dataset (for Wisconsin) and no indicators for different road types were used in the analysis, though the analysis has shown differences in safety trends between state maintained and local roads.

In another study done by Qin et al (2007), a spatial analysis was used to identify crash prone locations in winter seasons for the Wisconsin state using three years of accident and weather data (2000 to 2002). Entire state was divided into grids of five square kilometres. Snow related accidents were aggregated by each grid and a safety index called relative crash rate was defined as follows:

$$X_i = \frac{T_t - SN_i}{T_i} \quad \textbf{(2 – 2)}$$

where, X_i = relative snow-related crash rate of grid i,

T_i = total number of crashes over a season in grid i, and

SN_i = total number of snow-related crashes over a season in grid i.

Snow intensity in centimetres per day for each grid (SNI_i) was calculated by dividing the total yearly accumulated snow by the number of snow days in that grid. The relative accident rate was then plotted against the snow intensity and a power function was calibrated as shown in **Equation 2 – 3**.

$$X_i = 0.0025\ SNI_i^{0.7592} \qquad \textbf{(2 – 3)}$$

Qiu and Nixon (2008) conducted a meta-analysis based on past studies from 1967 to 2005. According to their review, snow precipitation was found to increase the total number of crashes by 73%, 85%, and 100% in average in USA, Canada and UK, respectively, whereas the corresponding change due to rain was 58%, 73%, and 24%. Similar pattern was observed for injury related crashes. It should be noted that these estimates are gross averages from different studies conducted in different countries and years. Variations in these percentages were attributed to many factors such as exposures, driving behaviours, and maintenance operations. High winds were also found to cause an increase in the traffic crash rate.

Andersson and Chapman (2011) investigated the effects of temperature (global warming) on winter road safety in West Midland, UK using two winter seasons data (2004-05 and 2005-06). Using UK climate impacts programme data for climate change scenarios they predicted that number of days per season with low temperatures will decrease due to global warming. To analyses the effects of these temperature changes they defined a collision risk factor given by the ratio A/D, where A = number of accidents at temperature T and D = number of days per winter at daily minimum temperature T. This ratio was calculated for the temperature range from -6 C to +6 C. This ratio was multiplied with the number of days in future year (2080) with the specific temperature. For days with temperature less than 5 C they found a 12% reduction in number of accidents due to reduction in the number of such days.

This study however assumes temperature to be the only factor affecting the change in accidents; however, accidents are affected by a number of other variables besides temperature. Global warming will not only affect temperature but also other environmental factors. This study do not considers the confounding effects of other variables. Moreover, the time span for this reduction is very large (70 years) where there could be many new innovations improving road safety conditions.

2.1.2 Traffic Effect on Safety

Traffic flow, commonly represented by total traffic volumes, vehicle kilometres traveled or combination of intersecting volumes, is a measure of opportunities or exposure for collision. Traffic has therefore a direct impact on the safety of a highway and is considered the most important variable explaining the variation of crashes between different sites and over time (Fridstrøm et al 1995; Lord 2002). It is almost customary to include of traffic related term such as exposure in accident prediction models (Van den Bossche et al. 2005). This fact is also evident from the many flow-only models in road safety research such as safety performance functions (SPF) in HSM (Highway Safety Manual). Due to this direct link, many past studies had focused on modeling accident rate, defined as ratio of accident frequency to exposure, instead of accident frequency, assuming that accident frequency is linearly proportional to traffic exposure. However, many researchers (Maher and Summersgill 1996; Andrew and Bared 1998; Lord and Persaud 2000; Garber and Ehrhart 2000; Lord 2002; Miaou and Lord 2003; Muhammad 2003; Roozenburg and Turner 2005; Mustakim et al 2006; Sayed and El-Basyouny 2006; Sayed and Lovegrove 2007; Jonsson et al 2007; Kononov et al 2008; and Lord and Geedipally 2008) have shown that traffic could have a non-linear effect on accident frequency. Roozenburg and Turner (2005) have shown that the magnitude of effect varies according to the different accident types such as rear end accidents or turning accidents etc. This non-linear effect is also documented in a study by the National Cooperative Highway Research Program (NCHRP Synthesis 295, 2001), which summarizes a list of past research related to traffic safety and volumes. Similarly research conducted at disaggregate temporal level (hour by hour) also confirmed the non-linear relation between traffic and safety (Ceder and Livneh 1978; Ceder and Livneh 1982; Martin 2002).

Another aspect of the relation between safety and traffic is that of using accident rate or number for measuring the safety of a road entity. A study by Kononov et al (2007) showed that accident rate could decrease with increase in traffic volumes. Their study was based on accident and traffic data from a section of 2-Lane, rural highway in mountainous Colorado. Between 1988 and 1991 when AADT of the highway was 3062, the average accident rate was 2.28 accidents per million vehicle-miles traveled. However, the average accident rate decreased to 1.24 over the period from 1991 to 1995 after a casino was built and the total AADT increased to 13000. Note that the accident frequency had increased from 60 in the pre casino period (4 years from 1988 to 1991) to 136 in the post casino period (4 years from 1991 to 1995).

Traffic could also have a positive effect on road safety under winter conditions. One reason could be the reduction in traffic volume under adverse weather conditions and lower operating speeds. Another reason could be that vehicular forces and heat emitted from vehicles can help melt snow and ice on road surface (Qiu 2008; Qiu and Nixon 2009). High traffic volumes therefore tend to help in restoring road surface conditions. For instance, Nixon (2001) showed that road surface friction was increased by traffic alone from 0.18 to 0.23. However, this result could also be attributed to the confounding effect of other factors on road surface conditions.

2.1.3 Maintenance Effect on Safety

Road safety under adverse winter conditions could be improved through timely and effective winter road maintenance. Winter road maintenance stands for all those operations, methods and procedures that are done to restore deteriorated road surface to some specified level of service. Different maintenance methods are employed in different situations. The most widely used methods include salting, sanding, direct liquid application and ploughing or some combination of them depending on the specific weather and road surface conditions. Broadly, maintenance activities can be divided into two types: reactive operations, such as snow removal (ploughing) and deicing (salting), and proactive operations, such as salting in advance of a pending storm – a strategy commonly called anti-icing. Proactive anti-icing treatments are increasingly used in practice because of their effectiveness in preventing snow and snow to form a bond with road surface. Details about maintenance regulations and highway classifications for MTO, municipalities in Ontario and Finland are given in MTO Maintenance Manual, 2003; Municipal Act 2001, regulation 239/02, Ontario; and Transport Association of Canada, 2008.

Hanbali (1992) conducted a study to compare the accidents rates before and after certain maintenance operations. They selected 570 miles of road (520 miles two lane undivided and 50 miles divided freeways) randomly in New York, Minnesota, and Wisconsin. Hourly traffic and accident data were obtained from these areas for 1990 and used to calculate accident rates. He compared the accident rates over varied number of hours before and after salting and found that, for divided highways, there was a significant difference in accident rate two hours before and after salting while for undivided highways the difference was significant over four hours. The study found 87% decrease in accident rate for two lane roads and 78% decrease for freeways.

Fu et al (2006) showed that anti-icing, pre-wet salting with ploughing and sanding have statistically significant effects on reducing the number of accidents.

2.1.4 Factors Affecting Severity of Accidents

Severity analysis is an integral part of safety analysis and becomes more important when the objective of the study is cost benefit analysis.

Accident severity can be modeled using three different approaches. The first approach is to incorporate severity into the frequency domain by modelling collision frequencies of different severity types directly (Bijleveld 2005; Ma and Kockelman 2006; Park and Lord, 2007; Ma et al 2008).

In the second approach, separate models are developed to relate the conditional probabilities of experiencing individual severity levels for a given collision to various factors (Shankar and Mannering 1996; Dissanayake and Lu 2002; Yao 2004; Saccomanno et al 1996; Wong et al 2008).

In the third approach severity ratios are determined from historical accident data (Edwards 1998). Accident frequency is then weighted by these ratios to determine the share of each severity level.

Different factors have different effects on severity based on the methodology, data and location. **Table 2-1** gives a general idea of effects of weather on injury severity of an accident. A positive sign indicates that increase in the value of the variable would result in a severe accident and vice versa. Effects of other factors on injury severity of an accident are given in Appendix H, Table H – 1 to H – 5.

Table 2-1: Effects of Weather Related Factors on Accident Severity

References	Rain	Snow/ Winter	Fog/ Wind /Visibility	Dry Weather	Icy/ Wet road	Precipitation intensity	Days with Precipitation	Sun light hours	Days with Frost (Thunderstorm)	Water film depth	Pavement Friction-increased	First snow of the month	Wind Speed
Fridstrøm and Ingebrigtsen (1991)	+	–										+	
Saccomanno et al (1996)			–		+								
Edwards (1998)	–		+										
Lee and Mannering (1999)		+ (Injury only)		–	+								
Quddus et al (2002)					–								
Donel and Mason (2004)	+	+			+								
Van den Bossche et al (2004)						+	+	+	– (+)				
Dissanayake (2004)								+					
Wang and Kockelman (2005)				+									
Lapparent (2006)				+									
Ulfarsson et al (2006)					+								
Hermans et al (2006)						+	+	+	– (+)				
Deng et al (2006)					+								
Milton et al (2008)		+									–		
Jung et al (2009)										–			
Andrey (2010)	+	+											
Quddus et al (2010)					–			+					
Mergia (2010)				+	+								
Jung et al (2010)													
Number of Studies	**4**	**5**	**2**	**4**	**8**	**2**	**3**	**4**	**2**	**1**	**1**	**1**	**1**
Effect (>50%)	**+**	**+**		**+**	**+**	**+**	**+**	**+**	**– (+)**	**–**	**–**	**+**	**-**
Effect (>85%)		**+**				**+**	**+**	**+**	**– (+)**	**–**	**–**	**+**	**-**
Effect (100%)						**+**	**+**	**+**	**– (+)**	**–**	**–**	**+**	**-**

2.2 Quantifying the Effects of Winter Road Maintenance on Road Safety

The previous section provides a general description on the effects of various factors on road safety. In this section, we focus specifically on the relationship between winter road safety and winter road maintenance, which is also the primary motivation of this research.

Norrman et al (2000) was among the first who attempted to quantify the relationship between road safety and road surface conditions. They compared crash rates associated with different road surface types using five years (1991 to 1996) collision and winter weather data from two RWIS stations within a radius of twenty five kilometres in the county of Halland, Sweden. Precipitation, temperature, relative humidity and wind were considered as part of the weather variables.

They classified road surface conditions into following ten different types based on slipperiness:

(1) Rain/sleet on a frozen road surface,
(2) Snow on a frozen road surface,
(3) Snow/sleet on a warm road surface,
(4) Snowfall together with hoarfrost,
(5) Hoarfrost and low visibility,
(6) Freezing dew followed by hoarfrost,
(7) Strong formation of hoarfrost,
(8) Weak formation of hoarfrost,
(9) Drifting snow, and
(10) Water cover which freezes.

The accident risk for a specific road surface condition type, A_T, is defined as the ratio of the accident rate to the expected number of accidents for each month (**Equation 2-4**).

$$A_T = \frac{1}{N} \sum_{m=Nov1991}^{Apr1996} \left(\frac{\left(\frac{A_{t,m}}{h_{t,m}} \right)}{\left(\frac{A_m}{h_m} \right)} \right) \qquad \textbf{(2 – 4)}$$

where N = the number of months, which was 18 in this study,

$A_{t,m}$ = Number of accidents that had occurred under road surface condition T in month m,

$h_{t,m}$ = Corresponding number of hours.

$A_{t,m}/h_{t,m}$ = Accident rate for road surface condition, type T.

A_m = All accidents during a month (evenly distributed events and not affected by different road conditions), and

h_m = Number of hours in that month.

A_m/h_m = Average number of accidents per hour.

A table was then developed showing percentage of accidents for each slipperiness type and the corresponding risk. It was found that Type 2 surface (Snow on a frozen road surface) had the highest rate of accidents, followed by Type 1 (Rain/sleet on a frozen road surface) and Type 4 (Snowfall together with hoarfrost) surfaces. These values were then compared to maintenance activities using a ratio defined as "the number of times maintenance was done at the time of a traffic accident" divided by "the total number of traffic accidents on that type of slipperiness". This ratio was 100% for type 1 (Rain/sleet on a frozen road surface) and Type 4 (Snowfall together with hoarfrost) whereas 65% for type 2 (Snow on a frozen road surface). These values show that even with 100% maintenance, such as for Type 1 (Rain/sleet on a frozen road surface) and Type 4 (Snowfall together with hoarfrost), accidents will occur. On the other hand, it shows that increasing maintenance will reduce the number of accidents as in Type 2 (Snow on a frozen road surface).

The approach taken by this study (Norrman et al. 2000) has several limitations. First of all, it is an aggregate analysis in nature, considering roads of all classes and locations together. This aggregation process may average out some important environmental and operating factors that affect road safety at a local level and therefore the results may not be applicable for assessing decisions at an operation level with an analysis scope of a maintenance yard. Secondly, the simple categorical method of determining crash rates may introduce significant biases if confounding factors exist, which is likely the case for a system as complex as highway traffic. Furthermore, the procedure cannot be used to compare the effect of different maintenance operations.

Recently, Fu et al (2006) investigated the relationship between road safety and various weather and maintenance factors, including air temperature, total precipitation, and type and amount of maintenance operations. Two sections of highway 401 were considered. They used Generalized Linear regression

Model (Poisson distribution) for analyzing the effects of different factors on safety. The resulting model developed for a maintenance route on Highway 401 is given in **Equation 2-5**.

$$\ln(\mu) = -0.671 + 0.069\,T + 0.127\,P - 0.007\,AI_1 - 0.001\,PW\_PS_1 - 0.007\,SD_1 \qquad \textbf{(2 – 5)}$$

where ,

μ = Mean number of accidents

T = Average of the min and max temperature (C).

P = Total precipitation (mm)

AI_1 = Anti-Icing – Total lane-km

PW_S_1 = Combination of sanding and salting) - Total lane-km

SD_1 = Sanding – Total lane-km

They concluded that anti-icing, pre-wet salting with ploughing and sanding have statistically significant effects on reducing the number of accidents. Both temperature and precipitation were found to have significant effect on the number of crashes.

Their study also suffers several limitations. First, the data used in their study were aggregated on a daily basis, assuming uniform road weather conditions over time of day for each day. Secondly, their study could not account for some important factors due to data problems, such as traffic exposure and road surface conditions. Furthermore, the data available for their analysis covered only 9 winter months and thus the power of the resulting model need to be further validated. One of the implications of these limitations is that their results are not directly applicable for quantifying the mobility benefit of winter road maintenance of other highways or maintenance routes.

Qiu (2008) and Qiu and Nixon (2009) used Multiple Classification Analysis for the effects of weather and maintenance on safety. Occurrence of collision within an hour was coded as a binary variable. Separate models were developed for accident frequency and severity. A stepwise modelling approach was utilised and three different models were developed. To model 1 independent variables such as road attributes (road classification, speed limit, urban/rural setting, AADT), weather (different stages of winter precipitation (before, during or after snow storm), wind speed, road surface temperature, and visibility) and maintenance factors (winter maintenance level of service, whether maintenance has been performed, ploughing, sanding, and chemical application) added. For the model 2, road surface conditions were added to the variables in model 1 and for model 3, traffic volume and speed variance were further added to model 2. Effects of a variable (e.g. road surface conditions) were calculated as the difference between the two models with and without that variable (model 1 and model 2). RSC was found significant in both frequency and severity models. With snow covered road the probability of injury and PDO crashes were 76% and 98% above the average, respectively. Snow storms were found to increase the probability of injury and PDO crashes by 95% and 33% above the average. Wind speed in the range of 12-15 mph was found to have the most effect, increasing the probability of injury and PDO crashes by 160% and 30% above the average. Inclusion of traffic volume and speed reduced the effect of road surface condition and precipitation by 7% and surface temperature by 8%.

A study in Finland (Leppänen, 1996) found that reduction of salt (from 6 to 7 T/road-km to 1.8 T/road-km) was associated with an approximate 5% increase in the number of injury accidents for highways with traffic greater than 6000 vehicles per day and 20% for low volume highways (salt reduced from 6 to 7 T/road-km to 1 T/road-km).

Nordic countries have conducted extensive research on issues related to winter road safety and road maintenance. However, most of these studies were published in the form of project reports in local language and few were made to academic journals. Wallman et al (1997) provided a comprehensive review on this body of work and the main findings can be summarized as follows:

- Accident rate is about 2 ~ 20 times higher on icy/snowy roads than those under BP (Anderson 1978).
- Accident rate is about 1.5 ~ 2 times higher for unsalted roads compared with salted roads (Brüde, Larsson 1981).
- Different road surfaces have different accident risk compare to BP (Schandersson 1986b) such as
    - Loose snow/ Slush 30 ~ 50 times higher
    - Packed snow/ Ice 8 ~ 12 times higher
    - Patches of snow and/ or Snow 10 ~ 15 times higher
- Accident rate is about 2 times higher when temperature is below – 1^{o} C than when it is above 0^{o} C (Polvinen 1987).
- Accident rate for multilane divided free way is about 4.5 times higher before salting than after salting and winter maintenance reduce traffic accident cost by about 85%. These figures increase to 8 and 88% for two lane highways respectively (Kuemmel and Hanbali 1993).
- The accident rate reached its maximum one hour before the maintenance action and the accident rate was reduced by 50 percent in half an hour after the action. The number of accidents was reduced to 1/6 6-12 hours after winter maintenance was implemented. They also cited that the

numbers of accidents were reduced up to 1/5 and 1/8 after maintenance was carried out in Germany and U.S., respectively.

- Sanding/ Salting reduces accident rates by about 50% due to increased friction and in one experiment (before and after analysis) resulted in a cost benefit ratio of 46 (Vaa, 1996).

Note again, the sources of the original studies where these statistics were obtained are difficult to trace as they were written in other languages in the form of research reports instead of peer reviewed publications. However, in terms of research methodology, most of these studies relied on simple comparative analyses - which are limited in their ability to account for different confounding factors, instead of rigorous statistical modeling. Nevertheless, the findings were in general consistent, showing that winter weather increases the risk of accidents by virtue of poor road surface conditions and that maintenance lowers crash risk by improving road surface conditions.

2.3 Statistical Modeling for Collision Frequency

As indicated in Introduction section, winter road safety is an important research issue of highway safety. Highway safety has been an area of intensive research over the past few decades. Many analysis approaches have been proposed, such as Before and after analysis (NCHRP, 2001; Geurts and Wets, 2003; empirical bayes method (Persaud et al. 2001; Hauer et al. 2002; Sharma and Datta 2007), safety performance functions (Kononov and Allery, 2003), simple linear regression (Valli 2005, Hong et al. 2005, Mustakim et al. 2006), generalized linear models (Andrew and Bared 1998; Muhammad 2003; Mustakim et al. 2006; Sayed and El-Basyouny 2006; Sayed and Lovegrove 2007; Jonsson et al 2007; Lord and Geedipally 2008), generalized estimating equations (Lord and Persaud 2000), hierarchical Poisson models (Miranda-Moreno 2006), spatial analysis (Qin et al. 2007), logit models (Saccomanno et al. 1996), time series models (Brijis et al. 2007; Quddus 2008a), and simulations (Sabel et al 2005; Andreas 2007). However, among them the statistical modeling approach remains to be the most successful and widely used because of its evidence based inference logic and availability of a rich set of model forms, ranging from simple linear equation to complex hierarchical model structures, for addressing diverse modeling challenges and data patterns. This body of literature will serve as the foundation of this research and is reviewed in the following section.

2.3.1 Standard Poisson Model

The most widely employed model for collision frequency is the generalized linear model commonly known as GLM technique (Knapp et al 2000; Roozenburg and Turner 2005; Muhammad 2003; Hermans et al 2006a; Qin et al 2006; Memon 2006; Sayed and El-Basyouny 2006; Qin et al 2007; Sayed and Lovegrove 2007; Jonsson et al 2007). As an extension of the linear regression models, GLM could be applied to model both continuous variables and discrete variables such as number of collisions on highways. For the later, which is of interest to this research, it is often assumed that collisions over a given period of time (year, month, day or hour) follows a count process such as Poisson distribution. Mathematically if the number of accidents (Y) is assumed to follow a Poisson distribution, then the probability of accident frequency can be expressed as shown in **Equation 2 – 6** (Cameron and Trivedi 1998).

$$P(Y = k) = \frac{e^{-\mu}\mu^{k}}{k!} \text{ , k = 0, 1, 2, 3 …} \qquad \textbf{(2 – 6)}$$

where, P (Y = k) = Probability of having k accidents over a given period,

Y= number of accidents over the same period

μ = expected number of accidents over the same period.

The model parameter μ in **Equation 2 – 6** is commonly assumed to be a function of different factors through a non-linear link function g (.), as shown in **Equation 2 – 7**.

$$g(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \qquad \textbf{(2 – 7)}$$

where

β_0 = intercept,

β_k = coefficient of explanatory variable X_k,

X_k = kth explanatory variable, which in the case of road safety could be factors related to road, weather and traffic characteristics.

The most commonly used link function in highway safety modeling is the log link function, which ensures positive estimates for the mean. Mathematically,

$$\ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \qquad \textbf{(2 – 8)}$$

OR

$$\mu = \exp(\beta_0 + \sum_{k=1}^{n} \beta_k X_k) \qquad \textbf{(2 – 9)}$$

Coefficients of explanatory variables can be estimated using maximum likelihood (ML) method based on the following ML function (**Equation 2 – 10**) (Cameron and Trivedi 1998):

$$\ell(\beta) = \sum_{i=1}^{n} [y_i \log(\mu_i) - \mu_i - \ln y_i!] \qquad \textbf{(2 – 10)}$$

where all the terms are as defined above. The coefficients β's are estimated by maximizing the function in **Equation 2 – 10** using numerical maximization methods such as Newton Raphson technique (Cameron and Trivedi 1998).

One of the important factors that influence collision frequency is exposure. Exposure can be expressed in terms of traffic volume, road segment length, or cross product of them. In a collision prediction model, exposure could be included either as a variable or as an offset. In the latter case **Equation 2 – 8** becomes:

$$\ln(\mu) = \beta_0 + \sum_{k=1}^{n} \beta_k X_k + \gamma \ln(EXP) \qquad \textbf{(2 – 11)}$$

where, *EXP* is the exposure and γ is the exponent of the exposure. Exposure in this research is defined as the product of traffic volume (total traffic volume in a snow storm event or hour) and the section length expressed in million vehicle kilometres.

Some researchers have used separate terms for different components of exposure (Qin et al. 2004; Miranda-Moreno 2006; Geedipally and Lord 2010), in which case **Equation 2 – 11** can be written as:

$$\ln(\mu) = \beta_0 + \sum_{k=1}^{n} \beta_k X_k + \gamma_1 \ln(EXP - traffic) + \gamma_2 \ln(EXP - length) \qquad \textbf{(2 – 12)}$$

where, *EXP - traffic* is the exposure measuring traffic and *EXP – length for length with* γ_1 and γ_2 as their exponents, respectively.

Depending on the type of distribution assumed for the collision frequency or severity, different models could be used as discussed in the following section.

2.3.2 Negative Binomial (NB) Regression Model

One limitation of the Poisson regression models is that the mean is assumed equal to the variance. However, in practice, the variance of accident frequency is often larger than its mean. This is known as the overdisperssion problem (Maher and Summersgill 1996; Cameron and Trivedi 1998; Lord and Mannering 2010). Statistically Pearson's Chi square statistic is used as over-dispersion test, which should be approximately equal to the residual degree of freedom (if over-dispersion does not exit) (Seavy at el, 2005). This means that if the ratio of Pearson's Chi square statistic divided by residual degree of freedom is close to 1.0 then the model is matching the data whereas a value of greater than 1.0 means overdisperssion. Over-dispersion can be either due to unobserved heterogeneity (Hauer 1997) or high count of zero accidents (Shankar et al 1997; Qin et al 2004).

Overdisperssion affects the standard error estimates of the covariates (Cameron and Trivedi 1998), making some insignificant variable significant. In safety literature this problem has been effectively addressed by using an alternative distribution such as Negative binomial (NB) and its extensions (Miranda-Moreno 2006).

Negative binomial (NB) models can be derived from the Poisson model structure by adding a Gamma distributed error term to **Equation 2 – 8**, that is,

$$\ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \xi \qquad \textbf{(2 – 13)}$$

where exp (ξ) is assumed to be Gamma distributed with both of its distribution parameters equal to φ. The resulting collision frequency (Y) should have a variance that is a function of the mean and φ as given in **Equation 2 – 14**.

$$Var = \mu + \varphi\mu^2 = \mu + \frac{\mu^2}{\alpha} \qquad \textbf{(2 – 14)}$$

Where $\alpha = 1/\ \varphi$ is the over dispersion parameter. Maximum likelihood method can be then used to estimate values of φ and coefficients (regression parameters) in the model. Exposure is treated in the same way as in Poisson model.

2.3.3 Generalized Negative Binomial (GNB) Regression Model

One of the shortcomings of the NB model is the assumption of a constant over-dispersion parameter (α) for all observations. This assumption can be relaxed by assuming that the dispersion parameter varies across locations as a function of a set of covariates. This will make the model capable of controlling for more heterogeneity than NB model. It has also been shown that using a varying dispersion parameter could improve model fit (Hauer 2001; Miauo and Lord 2003; Miranda-Moreno et al 2005; El-Basyouny and Sayed 2006; Miranda-Moreno and Fu 2006; Mitra and Washington 2007; Lord and Park 2008; Cafiso et al. 2010). For example, we could define α as a function of covariates as follows:

$$\alpha = \exp(\gamma_0 + \gamma_1 z_1 + \gamma_2 z_2 + \cdots + \gamma_k z_m) \qquad \textbf{(2 – 15)}$$

where $(z_{i1}, \ldots, z_{im})$ is a vector of factors that may be different from those for μ_i. The resulting model is commonly referred to as generalized Negative Binomial (GNB) model (Miaou and Lord 2003; Miranda-Moreno et al 2005; Miranda-Moreno 2006; Lord and Park 2008). This model may allow more flexibility than its alternatives to deal with the well known over-dispersion problem and unobserved heterogeneities among events.

2.3.4 Zero inflated Regression Model – Poisson (ZIP) and Negative Binomial (ZINB)

As described earlier, one source of over dispersion is presence of excess zeros. This is the case when the observed data has number of zeros in excess of those that could by modeled by the regular Poisson process (Cameron and Trivedi, 1998), thus violating the mean – variance equality assumption of the Poisson models. For these conditions models with dual state process have been suggested by researchers such as Lambert (1992), Miao (1994), Shankar et al. (1997), Carson and Mannering (2001), Kumara and

Chin (2003), Qin et al. (2004), Miranda-Moreno (2006), Miranda-Moreno and Fu (2006). These models are known as zero inflated models.

These models assumes a dual state process in accident occurrence: one generating safe events with zero accidents (Y~0 with probability p) and the other state following a Poisson or NB distribution [Y ~ Poisson (μ, α) with probability 1- p] or [Y ~ NB(μ, α) with probability 1- p] with the resulting models known as zero inflated Poisson (ZIP) or zero inflated NB (ZINB) models, respectively. These models may be more flexible compared to standard Poisson or NB models since they can handle both over-dispersion due to unobserved heterogeneity and excess of zero counts.

However these models have one drawback – the assumption of safe state. Accidents are random events which can happen anywhere and, as Hauer (1999) has pointed out, no highway is safe or unsafe in itself but some highways are safer than others. Therefore, researchers such as Lord et al (2004) and Lord et al (2007) have cautioned against the use of such models.

2.3.5 Poisson Lognormal Models (PLN)

When the error term in NB model is assumed to follow normal distribution instead of a gamma distribution, the resultant model structure is known as Poisson Lognormal (PLN) model which is capable of capturing the unobserved heterogeneity.

$$Y\,|\theta \sim \text{Poisson}\ (\theta) = \text{Poisson}\ (\mu\, e^{\varepsilon}) \qquad \textbf{(2 – 16)}$$

where ε ~Normal (0, σ^2) and e^{ε} ~ Lognormal (0, σ^2). This model has the advantage that it can be extended to deal with multi-level datasets. The multilevel model structure is necessary for some disaggregate data sets such as those used in this research. As discussed in Chapter 4, the disaggregate data set in our research is longitudinal in nature with the hourly records within each storm event forming a set of repeated measures over time, which is different than a panel data, with the number of time periods being constant for each location. The potential within-storm correlation can be then captured by a multilevel model (Miranda-Moreno 2006; Miranda-Moreno and Fu 2006). Moreover, the lognormal tails are known to be asymptotically heavier than those of the Gamma distribution (Kim et al 2002; Miranda-Moreno 2006). This can be the case when working with dataset in the presence of outliers. Some empirical evidences and other advantages of the PLN model are presented by Winkelmann (2003) who compared this model with NB and found that this model fitted better than the NB model for a particular dataset. Moreover, they account for over-dispersion and general correlation structure (El-Basyouny and Sayed 2009a, Lord and Mannering 2010).

In addition to the models described above, a number of other models have been used by different researchers for collision frequency modeling. Some of these models are given in Appendix I, Table I – 1.

2.4 Statistical Models for Injury Severity

2.4.1 Binary Logit Models (BLM)

In collision severity analysis, the dependent variable is often in a binary form, representing two mutually exclusive injury outcomes of a given collision. The modeling approach used for this type of dependent variables is known as binary Logit model where the log link function in **Equation 2 – 7** is replaced by a Logit one, as follows:

$$\ln\left[\frac{p(y=1)}{p(y=0)}\right]=\beta_0+\sum_{k=1}^{n}\beta_k X_k \qquad \textbf{(2 – 17)}$$

Many researchers have used binary Logit models for accident severity analysis (e.g. Nassar et al 1994; Saccomanno et al 1996; Shankar et al 1996; Carson and Mannering 2001; Dissanayake and Lu 2002; Jones and Jørgensen 2003; Donnell and Mason 2004; Shankar et al 2005; Lenguerrand et al. 2006; Milton et al 2008; Lee and Abdel-Aty 2008).

2.4.2 Multinomial Logit Models (MLM)

In some cases, however, more than two categories of accident injuries or consequences are of interest. The resulting model is known as multinomial Logit model. In this model, a base category of injury severity level is selected out of the different outcomes and other categories are estimated with respect to the base category. If there are three severity levels represented by 0, 1, and 2 with 0 as the reference or base category, then **Equation 2 – 17** can be further written as:

$$\ln\left[\frac{p(y=1/X)}{p(y=0/X)}\right] = \beta_0 + \sum_{n=1}^{N} \beta_n X_n$$

$$\ln\left[\frac{p(y=2/X)}{p(y=0/X)}\right] = \beta_0 + \sum_{n=1}^{N} \beta_n X_n \qquad \textbf{(2 - 18)}$$

Many researchers have used multinomial Logit models for accident severity analysis (Shankar and Mannering 1996; Lee and Mannering 1999; Lee and Mannering 2002; Ulfarsson and Mannering 2004; Holdridge et al 2005; Khorashadi et al 2005; Ulfarsson et al 2006; Malyshkina and Mannering 2008; Miranda-Moreno et al 2009; Mergia 2010.

2.4.3 Ordered Logit Models (OLM)

Ordered Logit models (OLM) is an extension of MLM to account for the inherent ordering of severity levels in collisions, such as, from property damage to injure and to fatal (O'Donnell and Connor 1996; Khattak et al. 1998; Srinivasan 2002; Wang and Kockelman 2005; Savolainen and Mannering 2007; Mergia 2010; Quddus et al. 2010; Zhang 2010). Let Y denote the observed severity level, Y* the unobserved injury severity level and μ_1, μ_2… μ_j the cut-off points or threshold values for the injury severity levels, then

Y = 1 if $Y^* \leq \mu_1$

Y = 2 if $\mu_1 < Y^* \leq \mu_2$

.

.

.

Y = j if $\mu_{j-1} < Y^*$

Where j represents the number of injury severity categories. Assume Y* is a function of a set of covariates as shown in **Equation 2 – 19** (Liao 1994; Wang and Kockelman 2005), then

$$Y^* = \ln\left[\frac{Severity^s}{Severity^r}\right] = \sum_{k=1}^{K}\beta_k X_k + \varepsilon \qquad \textbf{(2 – 19)}$$

Where, β_k are model coefficients to be estimated and $\{X_1, X_2, \ldots. X_k\}$ represents a set of explanatory variables. ε is assumed to be logistic distributed. Severity with superscript "r" represents the base severity against which other severity levels, denoted by superscript "s", are compared. The reference category could be either the least or most severe one. The probability of a particular injury severity level Y = j can be estimated using **Equation 2 – 20** (Liao 1994; Wang and Kockelman 2005), which can be further rewritten as **Equation 2 – 21** (Train 2009).

$$P(Y = j) = P(\mu_{j-1} < Y^* < \mu_j) = F\left[\mu_j - \sum_{k=1}^{K}\beta_k X_k\right] - F\left[\mu_{j-1} - \sum_{k=1}^{K}\beta_k X_k\right] \qquad \textbf{(2 – 20)}$$

$$P(Y = j) = P(\mu_{j-1} < Y^* < \mu_j) = \frac{e^{\mu_j - \sum_{k=1}^{K}\beta_k X_k}}{1 + e^{\mu_j - \sum_{k=1}^{K}\beta_k X_k}} - \frac{e^{\mu_{j-1} - \sum_{k=1}^{K}\beta_k X_k}}{1 + e^{\mu_{j-1} - \sum_{k=1}^{K}\beta_k X_k}} \qquad \textbf{(2 – 21)}$$

2.4.4 Multilevel / Hierarchical Logit Models

Collision data is hierarchical in nature where individuals or occupants are nested within vehicles and vehicles are nested within collisions. Because of the hierarchical nature of the data, there could be possible correlation at the occupant or vehicle level. Ignoring such correlation (intra class correlation) could result in under estimation of standard errors, thus causing some of the variables to appear falsely significant (Lee and Abdel-Aty 2008). This hierarchical structure has been recognized by different researchers such as Jones and Jorgensen (2003) and Lenguerrand et al. (2006).

In a multilevel setting, correlation at a sub level is taken care of by inclusion of random parameters which are constant within the sub level but are allowed to vary at the upper levels (Jones and Jorgensen 2003; Lenguerrand et al. 2006; Rasbash et al. 2009). In this section we will show how to extend binary logit models to a multilevel framework. We will consider random effects of intercept only. To extend the single level model (**Equation 2 – 17**) to for example a two level model where vehicles are nested within collisions we can rewrite **Equation 2 – 17** as follows:

$$\ln\left[\frac{p(y=1)}{p(y=0)}\right] = \beta_{0j} + \sum_{k=1}^{n} \beta_k X_{ijk} \qquad \textbf{(2 – 22)}$$

$$\beta_{0j} = \beta_0 + U_j \qquad \textbf{(2 – 23)}$$

where β_{0j} is the random intercept allowed to vary across different collisions at level "j". β_0 is a constant for different vehicles at level "i" within the level "j" and U_j is the variance by which this intercept is allowed to vary for different collisions at level "j". X_{ij} represents a set of covariates at the "ith" level differing from vehicle to vehicle.

In addition to the models described above, a number of other models have been used by different researchers for collision severity modeling. Some of these models are given in Appendix I, Table I – 2.

2.5 Model Assessment and Testing

As described in the previous section, many alternative models, differing in model forms and variables, are availed to model collisions. In order to determine which models are best for fitting the data, some test measures must be used to evaluate the goodness of fit of a model. This section reviews some of the major measures and tests.

2.5.1 Likelihood Ratio Test (T_{LR})

Likelihood ratio tests can be used to determine the goodness of fit of two different models fitted to the same data. The models to be evaluated must have a nested model structure, i.e., one model is a generalisation of the other (Cameron and Trivedi 1998). If λ is the ratio of the log likelihoods (LL) of two calibrated models: Model 1 and Model 2, then

$$\lambda = \text{LL (Model 1)/LL (Model 2)} \qquad \textbf{(2 – 24)}$$

$$\log \lambda = \log \text{LL(Model 1)} - \log \text{LL (Model 2)} \qquad \textbf{(2 – 25)}$$

$$-2 \log \lambda = -2 \text{ LL (Model 1)} - [-2 \text{ LL (Model 2)}] \qquad \textbf{(2 – 26)}$$

Most software packages, such as SPSS and Stata, give values of log likelihoods in the form of -2 LL. The null hypothesis H_0 can be formulated as follows:

***H_0**: No difference exists (Model 2 do not offer any improvements)*

The hypothesis test can be performed as follows: If -2 LL (Model 1) – [– 2 LL (Model 2)] > $\chi^2_{\alpha,n}$, where α = significance level (0.05) and n is the difference in the number of variables of the two models, then reject H_0 and select model 2; otherwise, Model 1 performs better and should be selected.

2.5.2 Akaike Information Criterion (AIC)

Akaike information criterion, proposed by Akaike (1974), is used to check the goodness of fit of different models, calibrated on the same data using maximum likelihood. AIC is defined as AIC = -2ln(LL)+2p, where LL is the log likelihood of a fitted model and p is the number of parameters, which is included to penalize models with higher number of parameters. A model with smaller AIC value represents a better overall fit. This is different from the LR test, the models being compared do not need to be nested, that is, they could be any models. Also, there is no critical value to compare to.

2.5.3 Vuong's Test

Vuong test, proposed by Vuong (1989), is another test used to check the goodness of fit of non-nested models such as zero inflated models compared to Poisson or NB models (Mannering and Lee 2002; Kumara and Chin 2003, Miranda-Moreno 2006). Vuong's statistic, however, does not impose penalty for additional model parameters. Vuong's statistic is given as:

$$V= \frac{\sqrt{n}\left[\frac{1}{n}\sum_{i=1}^{m} m_i\right]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} (m_i-\bar{m})^2}} = \frac{\sqrt{n}(\bar{m})}{S_m} \quad \textbf{(2 – 27)}$$

where $\bar{m}$ is the mean, S_m is the standard deviation, and n is the sample size. m_i is calculated as:

$$m_i = \ln\left(\frac{f_1(Y_i)}{f_2(Y_i)}\right) \quad \textbf{(2 – 28)}$$

where $f_1(Y_i)$ and $f_2(Y_i)$ are the probability density functions of the two models to be compared. V is asymptotically standard normal distributed and thus can be compared with z-values. A value of $|V| \geq V_{critical} = 1.96$ (using a 95% of confidence level) shows that the model represented by $f_2(Y_i)$ is better than that represented by $f_1(Y_i)$.

2.5.4 Comparison of Relative Frequency Distributions

Another approach to check the goodness of fit of a model is to compare the estimated relative accident frequencies from the model versus the observed (Maher and Summersgill, 1996; Miranda-Moreno 2006). A model goodness of fit can be measured by its match to the observed values.

2.6 Data Aggregation and Correlation Problems

In the road safety literature, the most common modelling approach is of single level using cross-sectional data aggregated by time (e.g., yearly or monthly) and by space (e.g., road segments or city-wise). Mostly this is due to unavailability of detailed data for analysis. Use of such aggregated data could suffer from several problems. Mensah and Hauer (1998) identified two major problems with such an approach. First, use of average values for a variable, though representing the average conditions for the day, season or year, does not truly represent the conditions at the time of accidents. Secondly, use of single level models might be troublesome if the data contains more than one group of highways.

Additionally there could be a potential bias in the parameter estimate associated with such parameters e.g. if we consider that a snow storm event lasted for 12 hours with very severe conditions in hour 3 and 4, an analysis based on the average values will be guided to a great extent by the two severe hours. On the contrary it is also possible that the effect of the two extreme hours is lost due to the averaging effects. Under such situations a disaggregate analysis will provide more realistic results.

One advantages of using aggregate data is that one doesn't have to worry about the possible within group correlation between observations and GLM are good candidate models for these conditions because these models assume that non-correlation exists between disaggregate observations (McCullagh and Nelder

1989; Maher and Summersgill 1996). This aggregation treatment addresses the issue of data correlation, but will likely result in loss of information and reduction in sample size (Hutchings et al., 2003).

The assumption of non-correlation could easily become questionable for many accident data sets which are commonly collected over consecutive periods of time at the same locations. In these data sets, observations are often clustered in a hierarchical or multilevel fashion with individual observations nested within groups – not necessarily in the form of panel data. In this situation, observations within a group are more likely to have some degree of correlation than those out of the group (Ronald and Thomas 2000; Newsom and Nishishiba 2002; West et al. 2007). This correlation when taken into account gives better results in terms of model fit (Aguero-Valverde and Jovanis, 2008) and will give biased results if ignored (Hutchings et al. 2003). In addition, some temporal trends can exist.

Unfortunately, single-level models ignore the potential within-period/group variations and the nested effect due to the repetition of observations belonging to the same locations. This can result in the loss of variability and potentially important explanatory information. For instance, when investigating the impact of weather (precipitation and temperature) and winter maintenance operations on safety, the variations of weather variables over short periods of time (hours or days) is likely to be highly influential in generating crashes. Model outcomes can be bias as a result of variations in the data that are not taken into account. This problem has been discussed by Washington et al., (2010) and Lord and Mannering (2010), recently. Despite the importance of this issue, very few empirical evidences exist on the data aggregation effect. Among the reasons, this could be because of the lack of disaggregate accident and traffic-related data.

The multilevel structure and aggregation problem has been recognized in other studies. For instance, Jones and Jorgensen (2003) and Lenguerrand et al. (2006) were among the first to recognize the need to consider the hierarchical crash-car-occupant structure of accident data for crash severity modelling. They discussed the potential issues of ignoring the clustering nature of data and the correlation within the clusters, such as erroneous estimates of model coefficients and understated standard errors and confidence intervals for the effects. Their conclusions were similar to those from other disciplines such as epidemiology, social research and political science (Ronald et al. 2000, Newsom and Nishishiba 2002, Hutchings et al. 2003, Aguero-Valverde and Jovanis, 2008, Gelman and Hill 2007). However, both studies focused only on the issue of data structure arising in modeling collision severity.

To measure the intra-class correlation (correlation among observations within the same cluster), the correlation coefficient (ICC), denoted by ρ, could be used. This coefficient with values ranging from 0 to

1 is calculated as the ratio of within group variance to the total variance (McGraw and Wong 1996; Newsom and Nishishiba 2002), as given in **Equation 2-29.**

$$\rho = \frac{\sigma_{wg}^2}{\sigma_g^2 + \sigma_{wg}^2} \qquad \textbf{(2 – 29)}$$

where σ_{wg}^2 is within group variance and σ_g^2 is between groups variance. For $\rho = 0$, single and multilevel models will have no difference in results. ρ equals to 0 if all collision counts within a class are independent of one another. On the other hand, if observations inside each cluster are exactly the same, then $\rho = 1$. Obviously, a $\rho \neq 0$ implies that the observations are not independent, i.e., the accident occurrence in the same cluster is influenced by similar unobserved factors.

Among the previous work dealing with temporal and/or spatial correlations, we can mention the work of Lord and Persaud (2000) that calibrated accident prediction models with data from 1990 to 1995 for four legged intersections in Toronto, Canada using generalised estimating equations (GEE) and NB with and without trend. Similar results were obtained except that the standard errors with GEE were greater than NB. An important effort on this issue is the one by Song et al. (2006) that developed Bayesian multivariate hierarchical models incorporating spatial effects through random parameters. They found that their model fit the data much better than Poisson regression models. Aguero-Valverde and Jovanis (2008) investigated the issue of spatial correlation and showed that accounting for spatial dependence can increase model fit. In another study, Quddus (2008b) investigated the issue of spatial dependence among the area-level crash observations and showed the need to extend conventional NB models to capture both spatial dependence and uncorrelated heterogeneity among neighbouring areas.

Jones and Jorgenson (2003) used multilevel models for accident severity analysis. They argued that with hierarchical data such as accidents with individuals nested within vehicles and vehicles nested within accidents, the observations are not independent. Accident data was obtained for all Norwegian roads from 1985 to 1996 with a total of 16,332 records comprising of serious, dangerous and fatal accidents. They found that GLM models perform worse than multilevel models when fitted to the same data set because the observations are not independent. Lenguerrand et al. (2006) proposed a hierarchical correlated structure to model severity with three levels: crash, car and occupant. To model accident severity, they tested three different methods: logistic models, generalized estimating equations (GEE), and multilevel logistic models, using accident data from 1996 to 2000 from the French road injury accident census. They found that the multilevel models yielded better results than the other two models, suggesting the importance of accounting for the observed correlation at the lower level. More recently, El-Basyouny and Sayed (2009a) used multivariate models to account for over-dispersion and correlation in accident severity and frequency. They argued that single level models are likely to omit the shared information/correlation among variables. They used three years of data for 99 signalized intersections in the city of Edmonton for the analysis.

2.7 Summary

This chapter provides a comprehensive review of literature on the important topics related to the area of winter road safety. It was found that most of the studies are devoted to investigating the effects of weather parameters on road safety. Furthermore, data used in most of these studies were highly aggregated both spatially and temporally. Such aggregation could mask the effects of some important factors and lead to biased parameter estimate and thus effect size, as described in the last section of this chapter. Lastly, most studies failed to take an explicit account of the effect of winter road maintenance operations and therefore the results cannot be applied for evaluating the benefit of alternative winter road maintenance policies, methods and operations. These issues are addressed by this research as detailed in the following chapters.

Chapter 3
METHODOLOGY

As described in Chapter 1, the primary goal of this research is to develop a quantitative understanding of the relationship between winter road safety and various factors related to weather, road surface condition, and traffic. The intent is to apply this knowledge to assess the implications of alternative maintenance policies on road safety. To achieve this objective, models must be developed that relate road safety effects of winter storms to road surface condition and other variables. This chapter details (1) the modeling and analysis methodology; (2) the data sources to be used in this research; and (3) the data processing and integration procedure to generate the data sets for the subsequent modeling.

3.1 Proposed Modeling Approach

A statistical modeling approach is proposed here to investigate the relationship between winter road safety and various possible influencing factors. **Figure 3-1** shows the steps being followed in the development of these statistical models, including:

1) Site selection: this is done based on the availability of weather & road surface, traffic and accident data (winter seasons only).
2) Data integration: hourly data from the different sources are integrated using date, time and location as the common reference.
3) Event formation: from the hourly data, snow storm events are extracted at the hourly level first and then subsequently aggregated at the event level. A snow storm event is defined from the start of the precipitation to the time when road surface conditions are restored to some pre-defined condition. The proposed modeling approach is also used to evaluate the effect of different aggregation levels and the impact of potential correlations among observations on the outcome of the analysis.
4) Exploratory data analysis and model development: as reviewed in Chapter 2, a number of alternative modeling techniques are available from the road safety literature and other fields; for the purpose of this research, however, we focus mainly the most popular approaches, namely, the traditional NB model and some of its extension such as the Generalized Negative binomial (GNB) and the Poisson-Lognormal (PLN) models.

More details on the data aggregation and modeling techniques used in each of these steps are provided in the following sections.

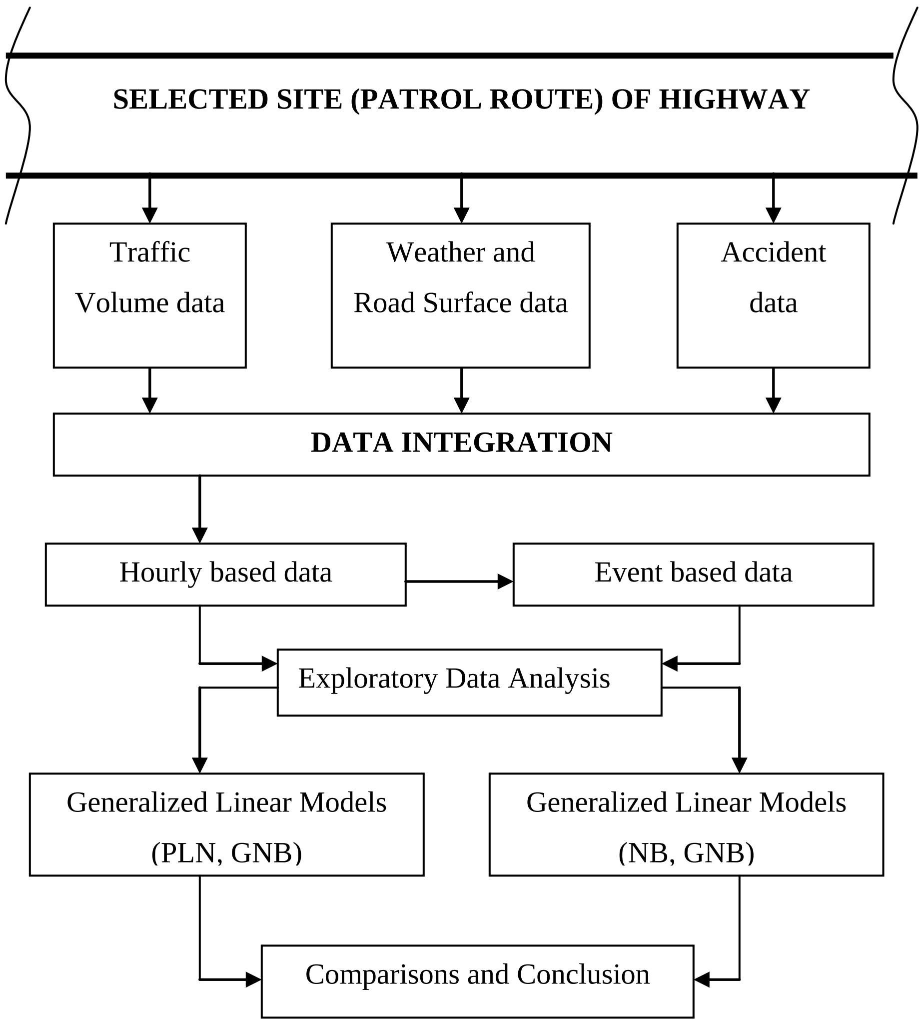

Figure 3-1: Modeling approach

3.1.1 Event-based Accident Models

To model collision occurrence under adverse winter conditions, we first conduct an event-based analysis focusing on collision frequency over individual snow storms. The data set used for this analysis includes event-by-event accident occurrence records along with all relevant weather, traffic, road surface and maintenance data aggregated or averaged by events (details on how this dataset was prepared are described in Section 3.3.2). The goal of this event-based analysis is to develop models that can explain the variation of collisions across different snow events. To achieve this objective, two different models are used, namely GNB and PLN (details in section 2.3). These models are considered because of their potential for addressing the over-dispersion problem that had been detected from this data set. Additional variables such as within season trends are also considered in the analysis. Details on the modeling results are discussed in Chapter 4.

3.1.2 Hourly-based Accident Models

The event-based analysis described above aggregates data (e.g. hourly observations) into event-by-event records. This aggregation process has two problems. First, it inevitably results in loss of information, i.e., the number of observations is reduced. Secondly, it may mask any variation of accidents and potential associated factors within the individual events. For example, over the duration of a snow storm, road weather and surface conditions could change dramatically, but are represented by some average measures in an event-based analysis. The same is true for winter road maintenance operations and accident occurrences. These problems could be addressed by considering a more disaggregate approach by using the hourly-based accident data directly. It should however be noted that the terms aggregate and disaggregate used in this research are relative to each other.

Along with single level GNB models, multilevel PLN models are used for the analysis of this data for their ability to account for the within storm correlation and hierarchical structure of the accident data. Accident trend within an event can be captured by including a time indicator, as shown in **Equation 3-1**.

$$Ln(\mu_i) = \sum \beta_i X_i + \alpha_1 t \qquad \textbf{(3 – 1)}$$

Where μ is the mean number of accidents, X is a set of variables influencing accident frequency, *t* is a binary variable (e.g., t = 1 if it is the first one or first two hours of the event, 0 otherwise) and β_i, α_1 are model parameters to be calibrated.

As with the event based data, additional variables such as within season trends are also considered in the analysis. A detailed discussion on this modeling approach is provided in Chapter 4.

3.1.3 Severity Models

Accident severity analysis is performed with the intention to investigate the effects of different variables on injury severity levels for collisions under adverse winter conditions and to develop predictive models for quantifying the collision consequences. Many of the severity studies in the literature have been performed using data aggregated to the accident level; however, accident reports often provide data at the occupant level, which could be valuable in providing additional explanation to the variation of collision severity. The aggregation process used in a collision level analysis could suffer the same problems as those of event based analysis described in Section 3.1.2. To examine the possible effects of such aggregation and develop the best fit models, three different model structures, namely, multilevel multinomial logit, multilevel ordered logit and multilevel binary logit, are calibrated and compared using three data sets representing three different aggregation levels: collision based records - one level including details on collisions but aggregated info about vehicles and occupants, vehicle based records - two levels including details on both collision and vehicle details but aggregated info about occupants, and occupant based records - three levels including details on collisions, vehicles and occupants. Chapter 5 provides a detailed discussion on these models and the modeling results.

3.1.4 Exploration of Physical-based Model Structure

Regression analysis in road safety analysis provides a mechanism to confirm the statistically significant association between an outcome (in this case, accident frequency or injury severity) and some independent variables (contributing factors). However, the association identified in a statistical analysis does not necessarily imply a causal relationship between an independent variable and the outcome. One approach to addressing this issue is to include the independent variable in a form that gives good physical interpretation. This section describes an attempt to include the road surface condition measure – coefficient of friction in such a way.

Coefficient of friction is one of the most comprehensive measures of road surface conditions, determining the maximum deceleration rate that a vehicle can use to slow down under emergency conditions and thus the stopping sight distance (SSD), as shown in **Equation 3-2** (NCHRP Report 400, 1997):

$$SSD = V \times t_{PR} + \frac{V^2}{2g(f \pm G)} \qquad \textbf{(3 – 2)}$$

where, SSD = stopping sight distance (m);

V = Vehicle speed (m/sec);

t_{PR} = Perception reaction time (sec);

f = Coefficient of friction;

G = Road grade (+ for uphill and vice versa); and,

g = gravitational acceleration (m/sec^2).

Equation 3-2 shows that SSD is inversely related to road surface friction (*f*). Some field studies have shown, however, that the actual SSD pattern as related to friction is somehow different from what is shown in **Equation 3-2**. For example, Oberg (Wallman et al 2001) has shown that drivers are not sensitive to a wide range of friction values. Based on an extensive review of past studies, they suggested that this non sensitivity is a failure, on the driver's part, to perceive actual friction and adjust their car-following headway. Lower SSD values than necessary for given friction values will lead to more collisions as the vehicles will not be able to stop before collision.

Ranck (2003) suggested an equation for estimating the number of accidents on a highway segment with restricted sight distance, in which the number of accidents is assumed to be a linear function of the length of highway with restricted SSD. In another study, Fitzpatrick et al. (2000) studied 439 accidents from 33 rural highways with speed limits of at least 55 mph in Illinois, Washington, and Texas (USA) and found that SSD was a potential contributor to accidents. Based on analysis of variance (ANOVA), they found that crashes were linked to SSD only when SSD was less than 95 meters, which means the relationship between accident frequency and SSD may be non-linear.

From this discussion, we propose the following functional form to be included in the collision frequency link function:

$$Ln(\mu) \propto \alpha_1 f^{\alpha_2} \qquad \textbf{(3 – 3)}$$

Where μ is the mean of accidents, *f* is coefficient of friction or an equivalent measure of road surface conditions and α_1, α_2 are model parameters to be calibrated.

Note that the model structure above is proposed based on the braking capabilities of vehicles. Other conditions can also be related to accidents in this manner for example, visibility. For low visibility, the length of a highway with restricted SSD will increase, which will increase the chances of accidents.

3.2 Study Sites and Data Sources

As described in Chapter 2, winter road safety is potentially related to a number of factors and, therefore, to investigate this relationship, historical information on both road accidents and these factors must first be obtained. This means that the study sites must be well instrumented so that detailed data on all major factors of interest are available. This section describes the study sites selected, various data sources and the pre-processing steps taken before entering the subsequent modeling step.

3.2.1 Study Sites

MTO has divided the province of Ontario into five different regions, namely, Central (CR), Eastern (ER), South-West (SWR), North-West (NWR) and North-East (NER). These regions are further subdivided into different contract areas. Each contract area contains multiple patrols and each patrol covers different routes. A route covered by a patrol for a particular highway is known as "patrol route" for that highway. Spatially, highway sections designated by these patrol routes are selected as the basic analysis units. To fulfil the purpose of this research a temporal aggregation level of one hour is considered as the minimum analysis unit. It was found that detailed hourly traffic data is not available for all the sites/patrol routes. Accordingly sites were selected where such data was available. Based on traffic data availability, a set of 34 sites were selected which were further reduced to 31 due to data unavailability from other data sources. Details of the selected sites are given in **Table 3 – 1** and **Figure 3-2**. Maps showing routes within each individual region are given in Appendix C.

Table 3-1: Selected Study Sites

Site	Location	Highway	Region	Class	Road Type	AADT Range	Length (Km)
Cochrane	Jct 655 14km east of Smooth Rock Falls to 26.2 Km west of smooth rock falls	11	NER	2	Kings - 2 lane undivided	2700~ 4400	68.1
Dunvegan	St Laurent Blvd to Quebec Border	417	ER	1	Freeway - 4 lane divided	10000~ 129000	114.7
Elliot Lake	Jct of Hwy 108 - Sec Hwy 639	108	NER	2	Kings - 2 lane undivided	400~ 2300	43.3
Gravenhurst	Gravenhurst 11 at Severn Bridge to Gravenhurst 11 at IC 117	11	NER	2	Kings - 4 lane divided	16100~ 22500	38.4

Table 3 – 1: Cont.

Site	Location	Highway	Region	Class	Road Type	AADT Range	Length (Km)
Kaladar	Heritage Line to Highway 41/4	7	ER	2	Kings - 2 lane undivided	2800~ 17700	98.5
Maple	Maple Leaf Dr. to Canal Road	400	CR	1	Freeway - 6 lanes divided	88400~ 194500	39.8
Massey	Hwy 17 - CR 4 to Sec Hwy 553 Imperial Street (Massey)	17	NER	2	Kings - 2 lane undivided	5000~ 9850	60
Morrisburg	Hwy 16 to Quebec Border	401	ER	1	Freeway - 4 lane divided	16000~ 20000	106.5
North Bay	Sunshine Lane to 12 Km North of Highway 64 Martin River	11	NER	2	Kings - 2 lane undivided	3900~ 7750	51
Carleton	Arnprior to March Rd	417	ER	1	Freeway - 8 lane divided	14600~ 16800	25.3
Kanata Patrol	March road to St Laurent Blvd	417	ER	1	Freeway - 8 lane divided	22000~ 158000	40.5
Port Hope	Newtonville to Trenton	401	CR	1	Freeway - 6 lanes divided	35500~ 48800	78.2
Port Severn	Port severn 400 at IC 153 Port Severn Rd to Port severn 400 at IC 207	400	NER	1	Freeway - 4 lane divided	7500~ 12500	53.3
Snelgrove	Snelgrove 10 at Collingwood Ave. to Snelgrove 10 at Broadway & Shelburne	10	CR	2	Kings - 4 lane divided	18300~ 21100	28.9
Grand Bend	From Grand bend 21 at IC 34 of 402 TO Grand bend 21 at IC 84	21	SW	2	Kings - 2 lane undivided	3150~ 6900	58.5
Kenora	Manitoba Border to the Vermilion Bay Patrol Yard (located 3.1 km West of the Hwy 647 Jct.)(Plus the Hwy 17A "Kenora By-Pass" which is 33.6 km)	17	NW	2	Kings - 2 lane undivided	1300~ 5000	105.2
Nipigon	Gorge Creek to Junction Hwy 587 on Highway 11	11	NW	2	Kings - 2 lane undivided	3850~ 5000	105
Shelburne	From Snelgrove 10 at Broadway and Shelburne TO Shelburne 10 at IC 4	10	SW	2	Kings - 4 lane undivided	5000~ 17800	60.41
Simcoe	Simcoe 3 at Dingle street to Simcoe 3 at Townline road	3	SW	2	Kings - 2 lane undivided	3950~ 8850	139.5
Sioux Narrows	From Hwy 11 to Govt Dock Rd (Sioux Narrows) - Berry/Dryberry Rd	71	NW	2	Kings - 2 lane undivided	970~ 1700	109

Table 3 – 1: Cont.

Site	Location	Highway	Region	Class	Road Type	AADT Range	Length (Km)
Shabauqua	Dog river road (5Km west of Raith on highway 17) Jct of hwy 11 and 17	17	NW	2	Kings - 2 lane undivided	1200~ 3700	36
Woodstock	Woodstock 401 at IC 195 to Woodstock 401 at IC 268	401	SW	1	Freeway - 4 lane divided	40000~ 67000	72.1
QEW 1	Burloak Dr to Centennial Pkwy	QEW	CR	1	Freeway - 8 lane divided	135000 ~ 175000	20.8
QEW 2	Centennial Pkwy to Victoria Ave	QEW	CR	1	Freeway - 6 lane divided	80000~ 100000	30.4
Highway 410	410 at IC 401 to 410 at IC BOVAIRD DR	410	CR	1	Freeway - 8 lane divided	116000 ~ 163000	12.9
Hwy 404	DVP to Green Lane	404	CR	1	Freeway - 10 to 6 lanes divided	35000 ~ 280000	37.2
Patrol 1	Harmony road to Morningside Ave	401	CR	1	Freeway - 13 lane divided - Core/Collec tor	104000 ~ 250000	32.3
Patrol 2	Morning side Ave to Hwy 400	401	CR	1	Freeway - 15 lane divided - Core/Collec tor	250000 ~ 430000	28
Patrol 3	Hwy 400 to Trafalgar Rd	401	CR	1	Freeway - 13 lane divided - Core/Collec tor	110000 ~ 430000	31.1
Patrol 4	Burloak Dr. to Erinmills Pkwy	QEW	CR	1	Freeway - 8 lane divided	124000 ~ 175000	17.4
Patrol 5	Erinmills Pkwy to Eastmall	QEW	CR	1	Freeway - 8 lane divided	129000 ~ 178000	13.1

Figure 3-2: Selected study sites.

After the sites were finalized, data collection was started. The time span selected for data collection was set to the period October 1999 to April 2010. However, due to unavailability of data from some sources, the final analysis period was restricted to the time frame of October 2000 to April 2006 (six winter seasons). Hourly data was obtained from each data source (details in the following section) for each site.

3.2.2 Data Sources

Road safety is directly affected by road surface conditions that in turn are affected by weather conditions and maintenance strategies. Weather conditions tend to deteriorate road surface conditions whereas winter road maintenance is an effort to bring the road surface conditions to the normal driving (bare pavement) conditions. Other factors such as traffic volume and road type are also of importance. To consider these factors in this research, five types of data sources were sought, including weather data, traffic data, accident data, road surface condition data and winter operations data. These data were gathered from different sources and managed by different organizations. This section provides a description of these data sources.

3.2.2.1 Traffic Volume Data

Traffic volume data for each study site is obtained from two sources. The first source is traffic data from MTO’s permanent data count stations (PDCS). PDCS provided traffic counts in different resolutions, including 15 minutes, 30 minutes, hourly and daily. Some of the stations also contained speed information. The PDCS sites used in this research are listed in Appendix D**.**

The second data source is from loop detectors. This data is collected at 20 seconds interval and contains information about speed, traffic flow and density. This data was provided in an hourly format by MTO for this research. The original data is organised by individual loop detectors. These loop detectors are located on Highway 400, 401, 404, 410 and QEW. Loops belonging to a particular patrol route on the highways mentioned were identified and processed together. Both data sources were screened for any outliers caused by detector malfunction.

Data Samples from the two sources are given in Appendix E where as the descriptive statistics are given in Appendix F.

Traffic volume distribution for the six seasons (2000-2006) for different regions (CR, ER, SWR, NER & NWR) is given in **Figure 3-3**.

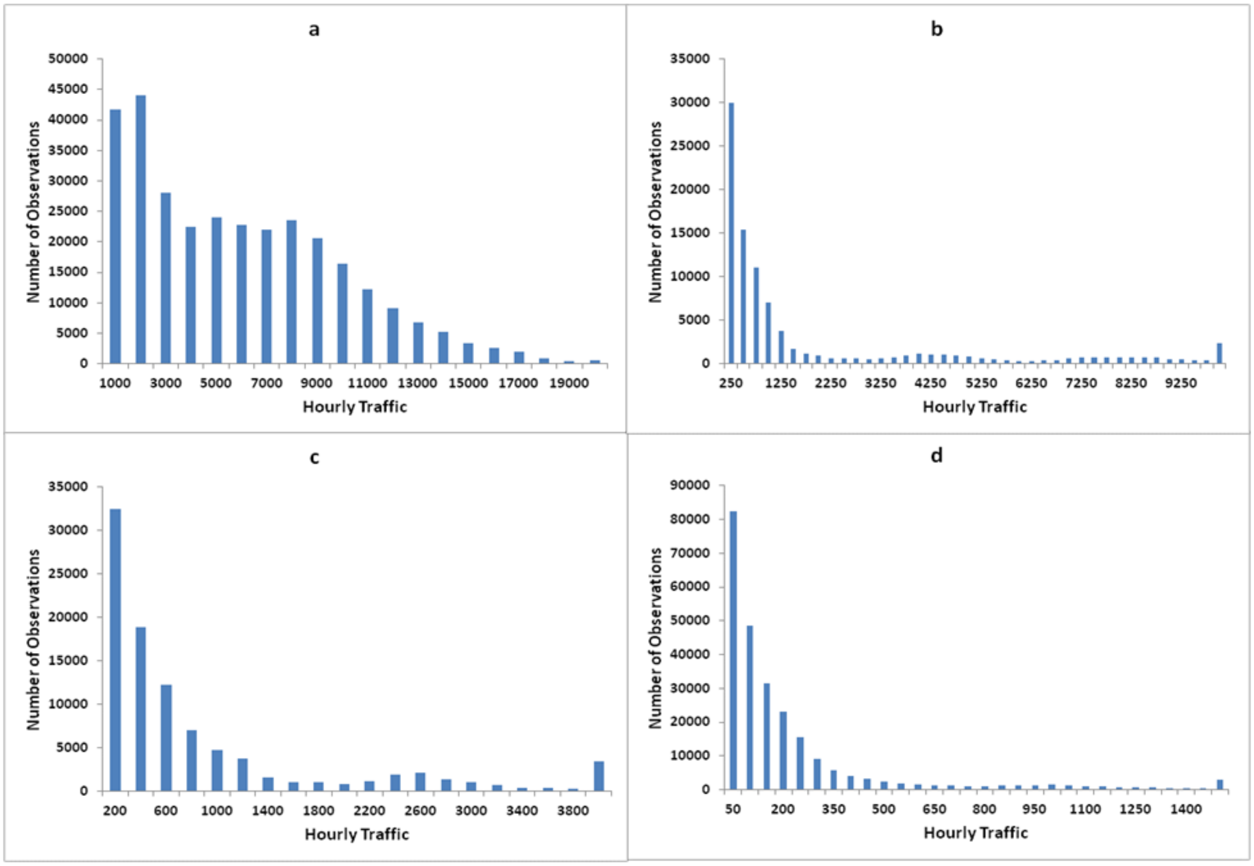

Figure 3-3: Regional distribution of hourly traffic volume (a=CR, b=ER, c=SWR, d=NER & NWR).

3.2.2.2 Traffic Accident Data

The Ontario Provincial Police (OPP) maintains a database of all collisions that have occurred on Ontario highways. This is "person based" data and includes information related to individuals as well as vehicles involved in each collision. A total of 147 variables are recorded. A database including all collision records for the study routes was obtained from MTO for the ten winter seasons (1999-2009).

The database includes detailed information on each collision, including:

- Accident time;
- Accident Location;
- Accident type;
- Impact type;
- Severity level;

- Vehicle information;
- Driver information;
- Road conditions – surface and geometry;
- Weather conditions;
- Speed; and,
- Visibility.

Note that the data on the accident occurrence time and location are needed for data aggregation over space (e.g., highway maintenance route) and time (e.g., by hour). The data items related to weather and road surface conditions represent only the conditions at the time and location associated with the observed collisions and therefore do not necessary represent the whole maintenance route. As a result, we did not use this data field directly and instead used it to complete any missing RSC data which was primarily sourced from MTO's road condition weather information system (RCWIS) and road weather information system (RWIS). Sample accident data is given in Appendix E. Distribution of accidents by site is provided in **Figure 3-4.** It can be observed from **Figure 3 – 4** that a large variation is present across the different sites. This variation could be attributed to the variation in traffic volume distribution as shown in **Figure 3 – 3** above.

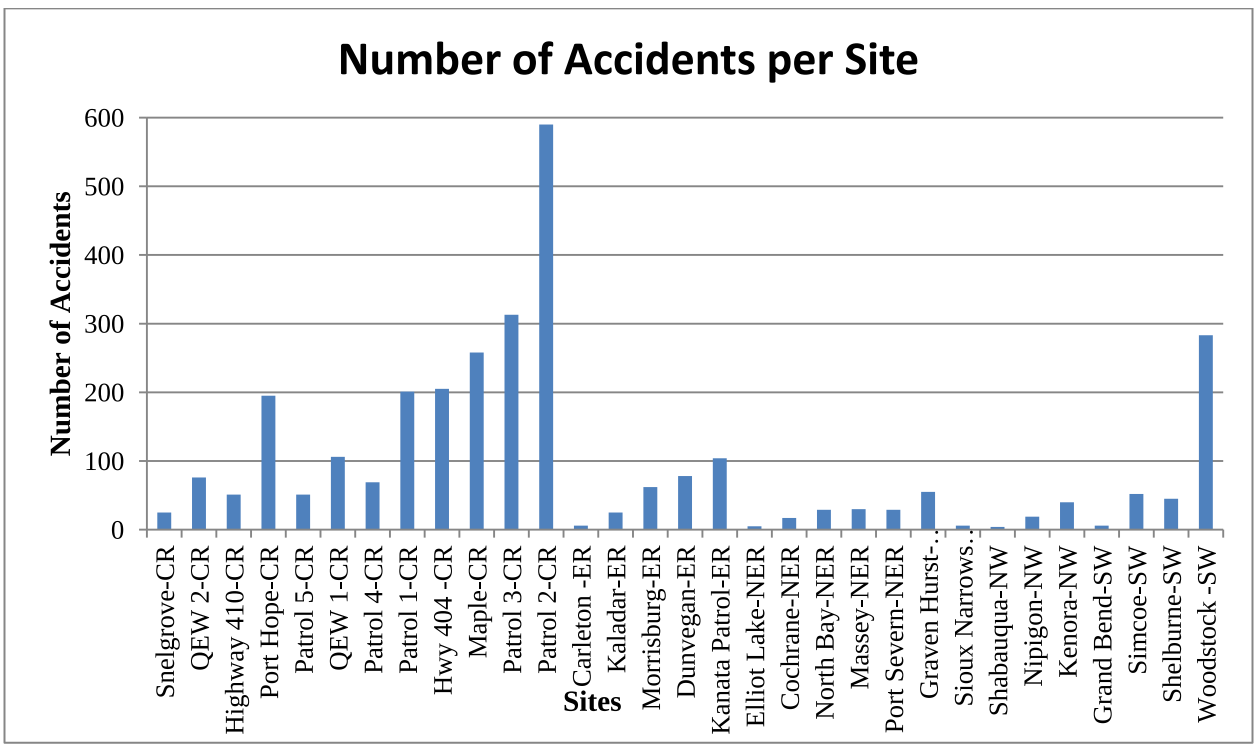

Figure 3-4: Distribution of accidents by site.

3.2.2.3 Road Condition Weather Information System (RCWIS) Data

This data contains information about road surface conditions, maintenance, precipitation type, accumulation, visibility and temperature. RCWIS data is collected by MTO maintenance personnel, who patrol the maintenance routes during storm events; 3 to 4 times on the average. Information from all patrol routes are conveyed to a central system six times a day. Instead of stations this data is collected for road sections. Each observation contains information regarding the section of road to which it belongs. One of the most important pieces of information in this data source is description of road surface condition, which is used in this study as a primary factor for accident modeling. A detailed description on this data field and its processing for the subsequent modeling analysis is given in later sections. This data is also used by MTO in their traveler's road information system; however, this is the first time that it has been utilized for research purposes. RCWIS data sample is given in Appendix E. A summary of snow storm events by sites is given in **Figure 3-5.**

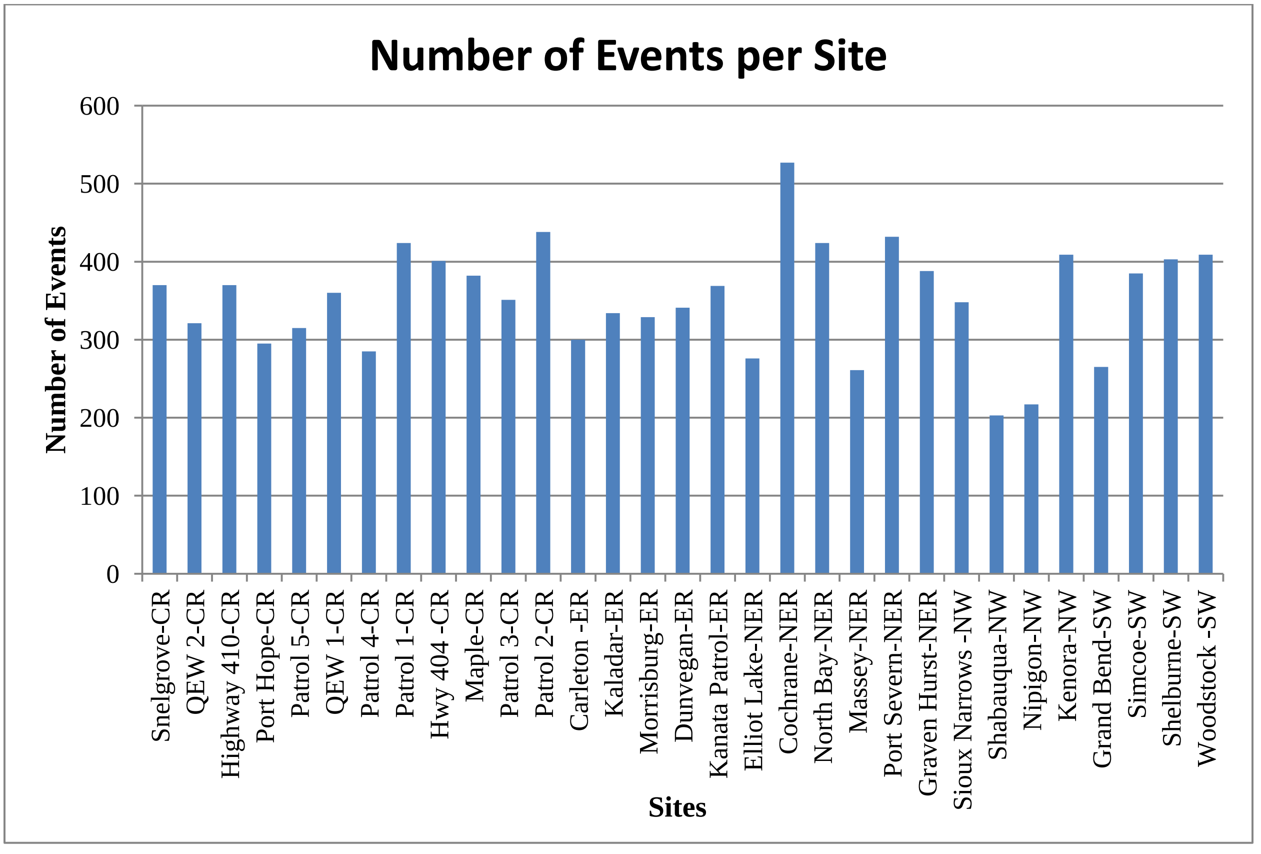

Figure 3-5: Distribution of snow storm events by sites.

3.2.2.4 Road Weather Information System (RWIS) Data

This data source contains information about temperature, precipitation type, visibility, wind speed, road surface conditions, etc., recorded by the RWIS stations near the selected maintenance routes. All data except precipitation were available on an hourly basis. Hourly precipitations from RWIS sensors were either not available or not reliable. As a result, we derive this information from the daily precipitation reported by Environment Canada (EC). Temperature and RSC data from RWIS were used to fill in the missing data from RCWIS. For visibility and wind speed RWIS was used as the primary source. RWIS stations record data every 20 minutes. The RWIS sites used in this research are listed in Appendix D where as in Appendix E sample data from RWIS station is given.

3.2.2.5 Environment Canada (EC) Data

Weather data from Environment Canada (EC) includes temperature, precipitation type and intensity, visibility and wind speed. Except precipitation related information, all data from this data source are used as a secondary source for filling in the missing data from RCWIS/RWIS. EC is the only reliable data source for precipitation type and intensity and it is therefore used as the primary source for these variables. Data is available at different time resolutions; but hourly data was selected for the purpose of this research. The EC sites used in this research are listed in Appendix D. In Appendix E, sample EC data is given whereas Appendix F documents the descriptive statistics for EC data.

3.3 Data Processing

As described previously, there are three main types of data available for each selected study site. Once these data were obtained, they were pre-processed for subsequent merging and integration. **Figure 3-6** shows the schematic used for processing and integrating the datasets from the available sources. Details on the steps involved are described in the following sections:

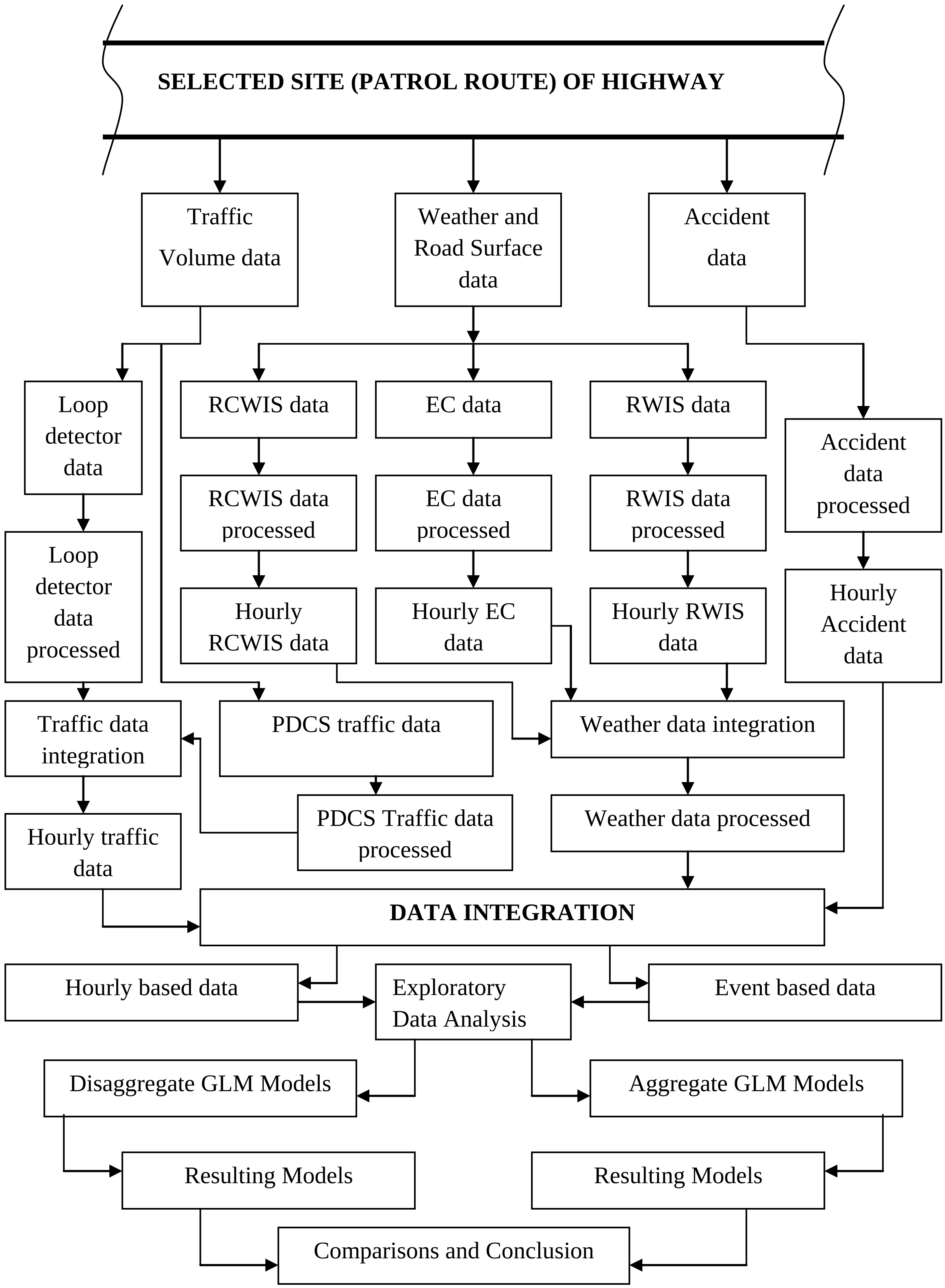

Figure 3-6: Data processing scheme

Traffic volume data: the traffic volume data is obtained from two sources: permanent data count stations (PDCS) sites, and loop detectors. Data from both sources is in hourly format; however, some pre-processing is required. These sources are used to supplement each other when data from one of the data source is missing. In cases where data is available from many loop detectors and/or PDCS sites, processing is done as shown in **Figure 3-7**. Data available for any section is summed over the cross-section, e.g., section A: sum of loops 1, 2, 3, 4 in **Figure 3-7**. This resultant sum is then averaged longitudinally (arithmetic average of data summed at section A, B, C and D) for the particular patrol route resulting in hourly traffic volume for that patrol route.

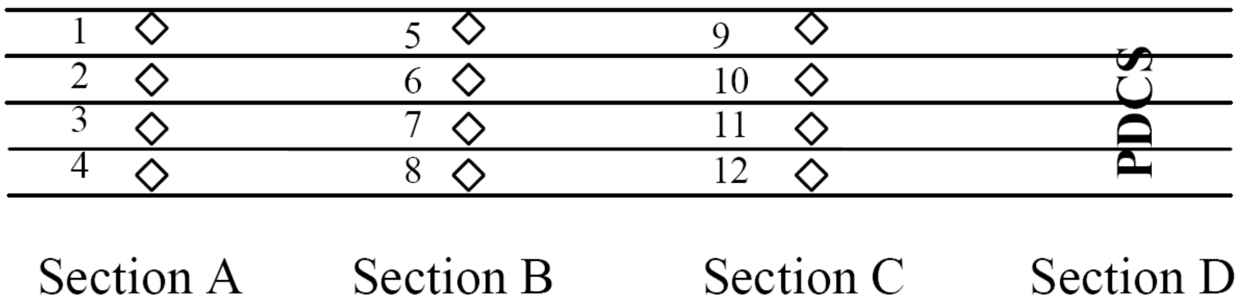

Figure 3-7: Traffic data processing scheme

Accident data: accident data is compiled as person/occupant based data (Note that person and occupant are used interchangeably in this research). Each observation in the data belongs to an individual person involved in an accident. A stepwise aggregation approach is used to compile this data into hourly records by totalling the accidents that occurred within each hour of the day. Other attributes associated with accidents are averaged for each hour, as shown in **Figure 3-8**. In the accident data (occupant based) each person and vehicle involved in an accident are identified uniquely. This dataset is first converted to vehicle based data, then to accident based data, and finally to hourly based data. These datasets are analysed separately for severity analysis and the results are discussed in Chapter 5.

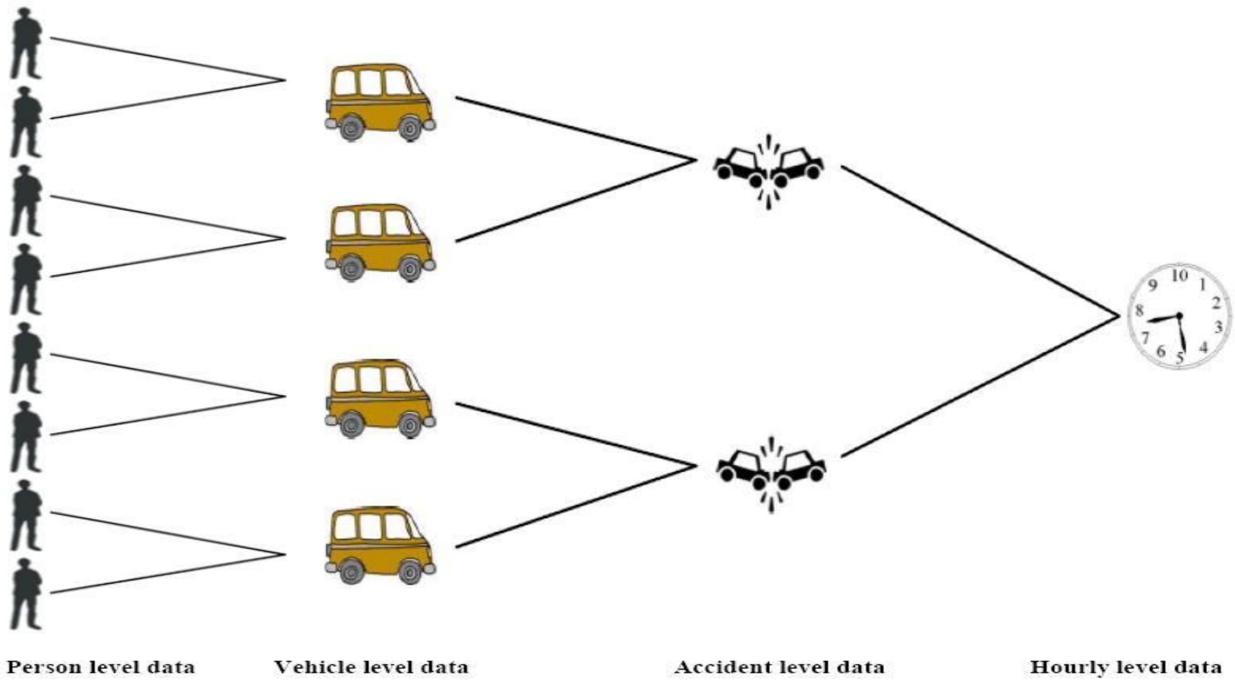

Figure 3-8: Accident data processing scheme

Weather and road surface data: weather data are obtained from three different sources: RCWIS, RWIS and EC. Most of the weather data from MTO's RCWIS is descriptive (or categorical) in nature. The data is thus coded to fulfill the specific purpose of this research. RCWIS data, organized by patrol route, is descriptive in nature, similar to event-based records with a time stamp. As a result, two immediate issues needed to be addressed. First, the original RCWIS data classifies road surface condition into seven major classes with a total of 486 sub-classes, making it difficult to use it as a categorical factor in a statistical analysis. Secondly there was missing information - a large number of hours did not have RCWIS observations. These issues were addressed by converting RSC to a scalar variable. This is discussed in detail in the following section. RCWIS data is converted to hourly data whenever the observations are available by taking the average of the variables within that hour and counting the number of different WRM operations performed within that hour. RWIS data is recorded every 20 minutes and is converted to hourly data by averaging observations within an hour. In cases that more than one RWIS stations are available for a single site, their average value is used. Data from Environment Canada is available in five different formats:

1) Data prefixed by MIN is hourly record of data recorded each minute;
2) Data prefixed by FIF is fifteen minute data;
3) Data prefixed by HLY is daily record of hourly data;

4) Data prefixed by DLY is monthly record of daily data; and,

5) Data prefixed by MLY is annual record of monthly data.

Hourly format is chosen as it suites our data needs. However, precipitation data is mostly available in the daily data-format, which is the water equivalent of the total precipitation amount over a day. Data was downloaded from Environment Canada website[1] for 389 stations. 217 Stations were selected based on their proximity to the sites. Out of these 217 stations were used in this research - 69 stations with hourly data and 171 stations with daily data (Precipitation data). These stations are selected using a two-step process (**Figure 3-9**). First, an arbitrary 60Km buffer is assumed around each site and sites falling within that boundary are selected. In the next and final step, stations closer to patrol routes are selected as control stations. Each control station is compared with other stations lying close to the control station using a paired t-test to determine whether stations distant from the control stations have a statistically different mean for each variable compared to the control stations. This step is necessary to select only stations with weather conditions similar to the control stations, which in turn represent the conditions at the patrol route. If, for a station, a variable, e.g., visibility is showing a significant difference in its mean from the mean visibility value of the control EC station near patrol route, the variable is removed. In the case that all variables show a significant difference, the whole station is discarded. Data from multiple stations are used to ensure that there are no missing values and to capture the average effects for a patrol route. Arithmetic mean is found to give better results than weighted average.

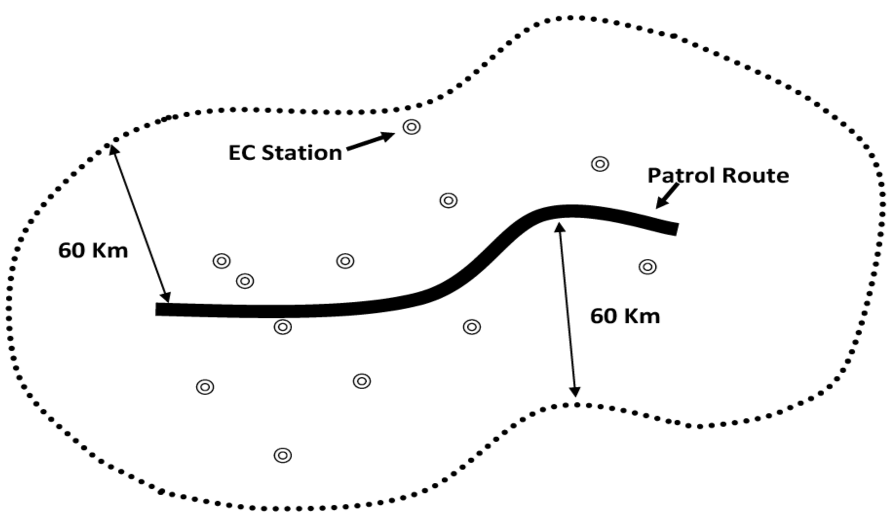

Figure 3-9: Identification of Environment Canada stations

[1] http://www.climate.weatheroffice.gc.ca/climateData/canada_e.html

Precipitation intensity data is available only as a daily total, which is the water equivalent of the total precipitation amount over a day. Based on the data describing "precipitation type" the hours with and without snow/freezing rain precipitation are identified. The total precipitation amount of each day is then uniformly allocated to the individual hours of the day during which precipitation occurred.

Once all the data's are converted into an hourly format, they are then fused into a single dataset on the basis of date (day), time (hour) and location (patrol route). Some of the variables in this dataset are duplicated as these variables are present in different data sources. In these cases priority is given to RCWIS data then RWIS data and then EC data because the former data sources are collected nearer the study sites and are therefore considered to be more representative. Similarly in case of any missing data for temperature, precipitation or wind in RCWIS, data from RWIS or EC data is used. Missing RSC data from RCWIS are retrieved from accident data or RWIS data. It is also assumed that the RSC for the hour directly following maintenance activities could be considered as at least partially snow covered. This data field is then subsequently linearly interpolated for hourly conditions, as discussed in the following section. This gives us values for road surface condition for all hours over individual storms. Once the three sources of data are finalized, a single dataset is formed by combining all datasets on the basis of date (day), time (hour) and location (patrol route). This process resulted in an hourly based dataset.

3.3.1 Modeling of Road Surface Conditions

MTO reports RSC using qualitative descriptions, i.e., a categorical measure[2] (with 7 major categories and 486 subcategories). These categories have intrinsic ordering in terms of severity, which means that a more analytically useful measure would be an ordinal one. While binary variables could be used to code ordinal data, it would mean loss of information in the ordering. We therefore decided to use an interval variable to map the RSC categories and at the same time make sure that the new variable would have physical interpretations. Road surface condition index (RSI), a surrogate measure of the commonly used friction level, was therefore introduced to represent different RSC classes described in RCWIS. The reason that we used a friction surrogate is that there have been a number of field studies available on the relationship between descriptive road surface conditions and friction, which provided the basis for us to determine boundary friction values for each category. To map the categorical RSC into RSI, the following procedure was used:

[2] http://www.ontarioweather.com/winter/roads/ontario/central.asp

1. The major classes of road surface conditions, defined in RCWIS, were first arranged according to their severity in an ascending order as follows:

   Bare and Dry < Bare and Wet < Slushy < Partly snow covered < Snow Covered < Snow Packed < Icy

   This order was also followed when sorting individual sub categories in a major class.

2. Road surface condition index (RSI) was defined for each major class of road surface state defined in the previous step as a range of values based on the literature in road surface condition discrimination using friction measurements (Wallman et al 1997; Wallman and Astrom 2001; NCHRP web document # 53, 2002; Transportation Association of Canada 2008; Feng et al 2010). For convenience of interpretation, RSI is assumed to be similar to road surface friction values and thus varies from 0.05 (poorest, e.g., ice covered) to 1.0 (best, e.g., bare and dry).

3. Each category in the major classes is assigned a specific RSI value. For this purpose, sub categories in each major category were sorted as per step 1 above. Linear interpolation was used to assign RSI values to the sub categories.

The RSI values for major road surface classes are given in **Table 3-2** and illustrated in **Figure 3-10**.

Table 3-2: Values Assigned to Different Classes of Road Surface Conditions

Road Surface Condition major classes	RSI from	RSI to	Number of Sub categories in a Class
Bare and Dry	0.90	1	75
Bare and Wet	0.80	0.90	80
Slushy	0.70	0.80	62
Partly Snow Covered	0.50	0.7	75
Snow Covered	0.30	0.50	64
Snow Packed	0.20	0.30	64
Icy	0.05	0.20	66

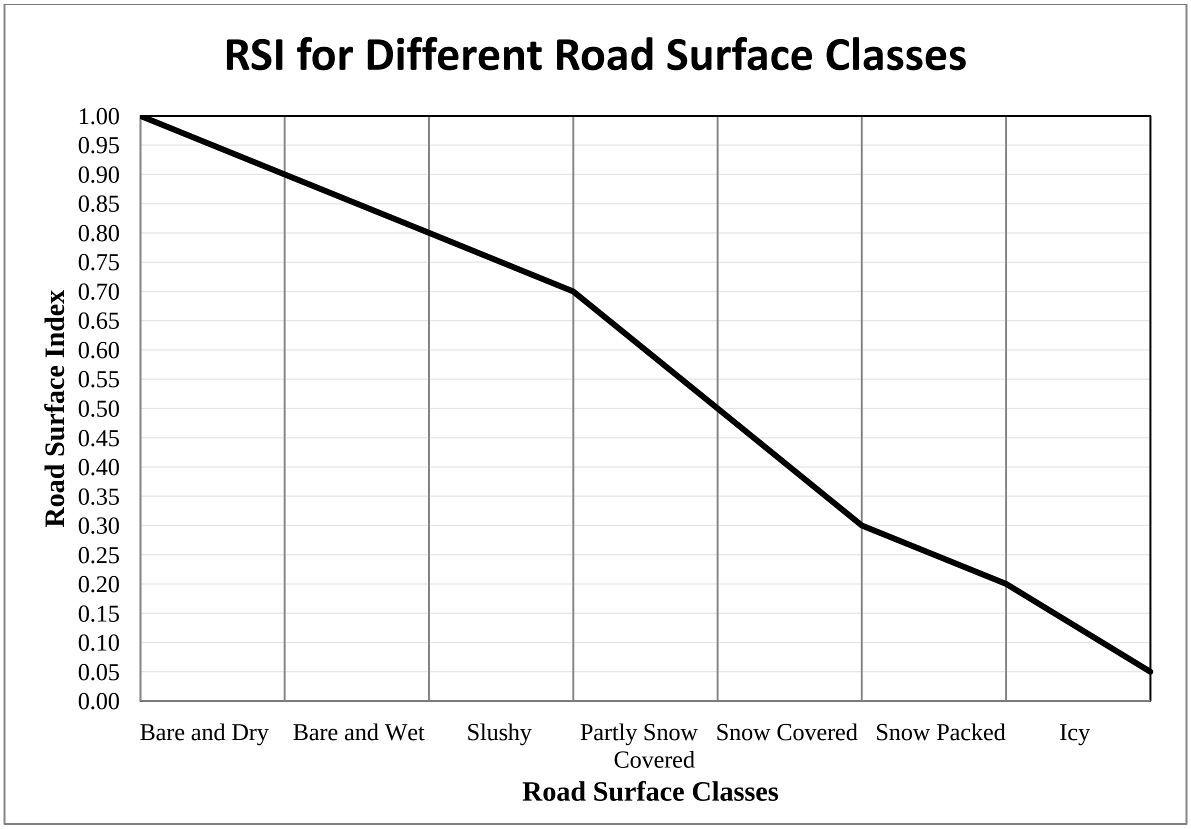

Figure 3-10: RSI for different road surface classes

3.3.2 Event Data Extraction

In the next step winter storm events are identified and a dataset of hourly based data (HBD) is formed by extracting hours corresponding to the identified events. The hourly events are then subsequently aggregated to generate an event-based dataset (EBD) by combining all hours of data over individual events. The events are defined on the basis of not only weather conditions but also of road surface conditions. This approach differs from other event-based studies where events are defined based on environmental data alone (e.g. Knapp et al 2000).

Each event is defined as follows:

- An event starts at the time when snow/freezing rain is observed/started;
- An event ends when snow/freezing rain stops and a certain predefined road surface condition is achieved after that time.

After extraction of events, the following additional constraints were defined for an event to be qualified for the analysis.

- Precipitation must be greater than zero (0 cm/hr)
- Air temperature must be less than 5 ^{0}C
- Road surface conditions index value must not be equal to bare dry conditions

This definition of storm events along with road weather, surface conditions and maintenance activities is schematically illustrated in **Figure 3-11**. A total of 10932 patrol events (events from now on) are extracted based on the event definition and restriction defined above. A total of 3035 collisions were observed in these events. These events are subsequently used for the analysis.

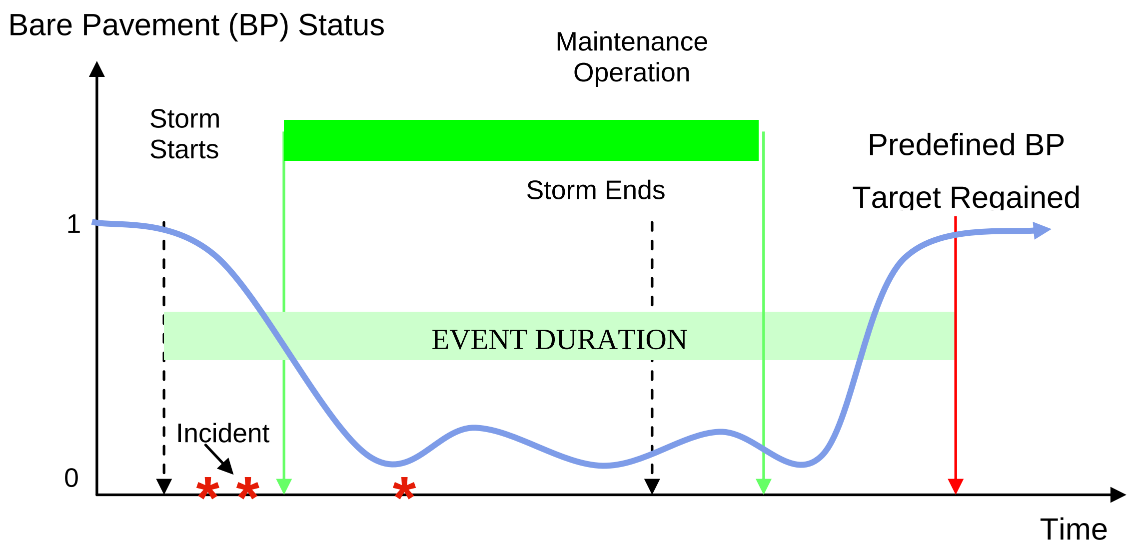

Figure 3-11: Road surface conditions and definition of snow storm event

3.4 Summary

This Chapter provides the methodology employed for this research as well discuss the various data sources considered in this research. Based on availability of data, 31 study sites were selected across the province of Ontario. These sites cover different levels of services, weather conditions and road surface conditions. Detailed data was obtained for each site from different sources such as traffic, accident, weather, winter maintenance and road surface conditions. These data's originate from different sources and have different formats. These data's were therefore pre-processed and then converted to hourly observations. All the data sources were combined into a single integrated dataset on hourly basis for each site using date, time and location as the common fields. Hourly events were extracted from this data and an hourly based event dataset was formed. Observations within an event were then averaged at the level of the event and another data dataset was created, namely, average event based data. These datasets were then used in the subsequent analysis as described in Chapter 4.

Chapter 4
ACCIDENT FREQUENCY ANALYSIS

Accident prediction models are developed in this chapter to associate accidents with a variety of variables related to traffic, weather factors, road surface and site-specific factors. The modeling techniques used for model development were based on the literature reviewed in Chapter 2, and the methodology described in Chapter 3. This research is based on an integrated dataset collected from 31 maintenance patrol routes as described in Chapter 3. Two different types of analyses are performed: event-based (aggregate) analysis, and hourly-based (disaggregate) analysis. Major conclusions and findings are summarized for each analysis type.

4.1 Data

Data used in this research was obtained from MTO and Environmental Canada, including accidents, weather, traffic volumes, road surface conditions and maintenance. This data corresponds to the period of October 2000 to April 2006. One of the characteristics of these data is that it differs in format and spatial and temporal coverage. For example, accidents, maintenance operations and road surface conditions are event data associated with a specific time while traffic and weather data are aggregated by a certain time interval (hours or day, for instance). For the convenience of this research, the data were first assembled and aggregated at the hourly level as described in chapter 3. Road surface conditions are represented using road surface index (RSI) based on the method described in Section 3.3.1. Snow storm events were subsequently extracted for each site. Snow storm events were identified as per Section 3.3.2. Therefore, the outcome of this process was two datasets, as described in Chapter 3, namely, event-based dataset (EBD) and hourly-based data (HBD). However HBD is in a disaggregated state while EBD was obtained by aggregating information for each event.

Table 4 – 1 and **Table 4 – 2** give a summary of snow storm events arranged by site and season respectively.

Table 4-1: Summary of Snow Storm Events by Site

Site	Number of Events	Average Event Duration (hr)	Average Temperature (C)	Average Wind Speed (Km/hr)	Visibility (Km)	Total Precipitation (cm)	Average RSI	Total Traffic	Number of Accidents	Number of Sanding operations	Number of Salting operations	Number of Ploughing operations
Sioux Narrows	348	12.02	-6.8	14.07	12.99	1234.29	0.7848	143594	6	325	1013	1091
Elliot Lake	276	12.36	-4.66	16.47	9.6	1890.07	0.7316	22954	5	329	504	534
Grand Bend	265	14.57	-3.43	19.61	13.13	1044.06	0.7442	381557	6	262	520	526
Carleton	300	9.2	-4.52	13.53	10.37	961.38	0.8156	2892316	6	10	504	445
Shabauqua	203	13.17	-6.38	11.21	14.04	1063.34	0.7566	180444	4	315	307	499
Cochrane	527	13.58	-8.81	13.87	14.22	2016.92	0.8112	380012	17	1455	1153	1887
North Bay	424	14.05	-5.44	15.18	11.76	2240.45	0.7806	493416	29	488	794	750
Massey	261	13.15	-5.53	14.99	12.65	1666.97	0.7711	463977	30	341	654	642
Nipigon	217	12.96	-7.44	11.42	0	834.91	0.7511	213270	19	347	462	532
Port Severn	432	10.87	-3.8	8.17	0	2291.89	0.775	843489	29	826	1248	1273
Graven Hurst	388	13.59	-4.46	14.36	10.1	2706.16	0.7366	2178354	55	1468	2042	1909
Kenora	409	12.6	-6.8	13.07	13.38	1230.87	0.8061	410835	40	675	1395	1544
Kaladar	334	10.66	-3.73	14.39	13.53	1200.05	0.7961	319516	25	199	1203	670
Snelgrove	370	10.42	-3.63	22.4	14.86	1584.44	0.7837	2809141	25	145	897	757
Simcoe	385	12.37	-3.59	15.6	13.62	1379.83	0.8068	984190	52	768	1493	1255
Shelburne	403	12.09	-4.27	12.3	11.05	2193.12	0.7397	1693256	45	1569	1979	2248
Morrisburg	329	8.72	-4.79	14.31	12.16	1126.18	0.8281	1769653	62	188	940	857
QEW 2	321	10.33	-2.99	15.84	13.02	1034.04	0.8449	9725391	76	54	371	195
Highway 410	370	9.78	-2.77	21.99	13.02	1098.8	0.8339	11290512	51	30	632	306
Dunvegan	341	9.23	-4.32	13.29	11.56	1269.5	0.8097	1947250	78	20	929	833
Port Hope	295	9.74	-2.6	15.55	12.53	936.19	0.8188	4058806	195	112	994	417
Patrol 5	315	9.48	-2.64	19.8	12.15	885.26	0.852	11003027	51	11	399	197
QEW 1	360	9.66	-2.72	16.07	11.74	984.17	0.8679	14411838	106	46	654	310

Table 4 – 1: Cont.

Site	Number of Events	Average Event Duration (hr)	Average Temperature (C)	Average Wind Speed (Km/hr)	Visibility (Km)	Total Precipitation (cm)	Average RSI	Total Traffic	Number of Accidents	Number of Sanding operations	Number of Salting operations	Number of Ploughing operations
Patrol 4	285	8.59	-2.59	14.93	12.17	841.38	0.8406	7630306	69	16	358	164
Kanata	369	9.62	-4.28	15.05	11.16	1195.86	0.8247	10913676	104	18	888	795
Woodstock	409	12.18	-3.74	16.84	11.45	1239.06	0.8045	5847701	283	451	1354	980
Patrol 1	424	9.39	-3.49	16.42	12.39	1255.91	0.8378	17941143	201	118	951	631
Hwy 404	401	10.25	-3.33	17.54	14.44	1460.91	0.8104	25926389	205	82	746	516
Maple	382	11.86	-3.13	19.32	14.39	1570	0.7958	18315571	258	73	741	477
Patrol 3	351	10.36	-3.07	21.16	12.61	1206.03	0.8087	25177767	313	41	939	483
Patrol 2	438	9.4	-3.38	18.18	13.86	1116.84	0.8308	19628705	590	44	501	317

Table 4-2: Summary of Snow Storm Events by Season

Season	Number of Events	Average Event Duration (hr)	Average Temperature (C)	Average Wind Speed (Km/hr)	Visibility (Km)	Total Precipitation (cm)	Average RSI	Total Traffic	Number of Accidents	Number of Sanding operations	Number of Salting operations	Number of Ploughing operations
2000/2001	1474	9.78	-3.73	16.25	11.91	4136.14	0.8738	36827674	395	254	778	616
2001/2002	1735	11.37	-3.19	18.32	12.24	6325.23	0.8128	19281519	420	1628	3365	2946
2002/2003	2263	12.57	-5.25	16.4	12.51	8030.88	0.7957	39628514	803	2517	6171	5160
2003/2004	1893	11.94	-4.55	17.94	11.91	6450.27	0.8042	38380618	540	2169	5928	4917
2004/2005	1832	11.72	-4.68	16.04	11.23	8178.95	0.7786	42656736	553	2151	6191	5392
2005/2006	1735	8.88	-4.03	9.19	11.1	9637.41	0.7586	23222995	324	2107	5132	5009

As part of the data needs, the following factors/variables were generated:

- Total number of accidents over the event/hour **[Dependent variable]**
- Event duration (in hours) **[EBD]**
- Indicator for month (October = 1, November = 2, December = 3, January = 4, February = 5, March = 6, April = 7) **[EBD, HBD]**
- SH (1 if first or second hour, 0 otherwise) **[HBD]**
- FH (1 if first hour, 0 otherwise) **[HBD]**
- Average[3] Air Temperature (C^o) **[EBD, HBD]**
- Average Wind speed (km/hr) **[EBD, HBD]**
- Average visibility (km) **[EBD, HBD]**
- Hourly precipitation (cm)**[HBD]**
- Total precipitation (cm)**[EBD]**
- Average RSI **[EBD, HBD]**
- Precipitation type (Freezing rain/ snow = 1, Other = 0) **[EBD, HBD]**
- WRM (sanding = 1, salting = 2, sanding + salting = 3, ploughing = 4, ploughing + sanding= 5, ploughing + salting = 6, ploughing+ sanding + salting = 7) **[EBD, HBD]**
- Anti-Icing (Yes = 1, No = 0) **[EBD]**
- Sanding (Yes = 1, No = 0) **[EBD, HBD]**
- Salting (Yes = 1, No = 0) **[EBD, HBD]**
- Ploughing (Yes = 1, No = 0) **[EBD, HBD]**
- Hourly Traffic Volume (vehicles/hr) **[HBD]**
- Bare Pavement Recovery (BPR) time (in hours) **[EBD]**
- Exposure (product of total traffic volume during the event and segment length, converted into million vehicle kilometres or MVKm for EBD. For HBD this was the product of segment length and hourly traffic, converted into Million vehicle kilometres or MVKm) **[EBD, HBD]**
- Traffic Exposure (Total traffic volume during the event or hour converted into million vehicle kilometres or MVKm) **[EBD, HBD]**
- Length Exposure **[EBD, HBD]**
- Site specific variable (Site or Region or Road Type) **[EBD, HBD]**

[3] Average for an event in case of EBD and hour in case of HBD

Month was included as a variable to test monthly trend over a season. To test the trend within snow storm, time factors were included in the analysis to check whether the start of the event is more susceptible to collisions compared to the rest of the snow storm. These factors were SH (for the effects of the first two hours against other hours in the snow storm) and FH (for the effects of the first hour against other hours in the snow storm).

Site specific effects were included in the models to take into account the potential effects of specific unmeasured factors on road safety, such as driver population, and road geometry.

For this purpose, three different fixed effects were investigated:

- Site-specific fixed effects using a dummy variable for each site
- Region-specific effects using a dummy variable for each region
- Road-type specific effects using a dummy variable for each road type

Ontario province is divided into 5 regions given below:

- Region 1 - Central Region,
- Region 2 - Eastern Region,
- Region 3 - North-Eastern Region,
- Region 4 - North-West Region, and
- Region 5 - South-Western Region

To control for the road type, a road classification was considered. This was done by classifying the sites under analysis into eight road categories. This was based on functional class, number of lanes and division as follows:

- Road Type 1 - Freeway - 13 to 15 lanes divided - Core/Collector,
- Road Type 2 - Freeway - 6 to 10 lanes divided,
- Road Type 3 - Freeway - 8 lanes divided,
- Road Type 4 - Freeway - 6 lanes divided,
- Road Type 5 - Freeway - 4 lanes divided,
- Road Type 6 - Kings - 4 lanes divided,

- Road Type 7 - Kings - 4 lanes undivided, and
- Road Type 8 - Kings - 2 lanes undivided

A number of two-way interactions were also tested for some of the variables for the analysis and those terms are listed below:

- Visibility x Precipitation type **[EBD, HBD]**
- Visibility x Precipitation **[EBD, HBD]**
- Wind Speed x Precipitation type **[EBD, HBD]**
- Wind Speed x Precipitation **[EBD, HBD]**
- Air Temperature x RSI **[EBD, HBD]**
- Event duration x RSI **[EBD]**
- Event duration x Precipitation type **[EBD]**
- Event duration x Precipitation **[EBD]**
- Exposure x Visibility **[EBD, HBD]**
- Exposure x RSI **[EBD, HBD]**
- Exposure x Precipitation type **[EBD, HBD]**
- Exposure x Precipitation **[EBD, HBD]**

Note that these interaction terms were identified on the basis of some possible physical interpretation. Higher level of interaction terms are not recommended in regression models due to the difficulty of the result interpretation. The interaction terms were however, found to be highly correlated (section 4.2) with their main effects and were therefore not considered for further analysis.

4.2 Exploratory Data Analysis

A total of 64 datasets (31 EBD, 31 HBD, EBD combined set, and HBD combined set) were formed for the 31 sites. Inconsistencies were verified through exploratory analysis. Descriptive statistics were computed for both EBD and HBD. Descriptive statistics for individual sites are given in Appendix – J and Appendix – K where the summary statistics are given in **Table 4 – 3** and **4 – 4** for EBD and HBD, respectively.

Correlation analysis was also conducted for each dataset. **Table 4 – 5** and **4 – 6** show the correlation coefficients between the interaction terms and their main factors for EBD combined set and HBD combined set. Based on these values, the interaction terms were excluded from further analysis. **Table 4 – 7** and **4 – 8** show the correlation matrix for other variables for the EBD combined dataset (EBD hereinafter) and HBD combined dataset (HBD hereinafter). Winter road maintenance (WRM) was found to be highly correlated with RSI in EBD and partially in HBD.

Table 4-3: Descriptive Statistics for EBD

	Temperature (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation (cm)	Accidents	RSI	Event Duration (hr)	Ln Exposure
Min	-29.87	0	0	0.02	0	0.247	2	4.87
Max	4.98	60.5	40.2	189.9	21	0.99	47	16.46
Average	-4.31	15.75	11.84	3.91	0.28	0.801	11.17	9.40
St.Dev	5.06	8.8	6.23	6.82	1	0.136	9.61	1.75
N	10932	10932	10932	10932	10932	10932	10932	10932

Table 4-4: Descriptive Statistics for HBD

	Accidents	Temperature (C)	Wind Speed (Km/hr)	Visibility (Km)	Hourly Ppt (cm)	RSI	Event Duration (hr)	Ln Exposure
Min	0	-33.55	0	0	0	0.05	2	3.77
Max	7	28	69	40.2	13.8	1	47	14.25
Average	0.020	-5.120	16.280	11.160	0.240	0.7457	19.44	8.03
St.Dev	0.180	5.560	9.620	7.910	0.370	0.1978	11.64	1.68
N	122058	122058	122058	122058	122058	122058	122058	122058

Table 4-5: Correlation Values for Two Way Interaction Terms (EBD Combined Dataset)

2-Way Interaction Variable	Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation type	Precipitation (cm)	RSI	Event Duration (hr)	Exposur e
Visibility x Precipitation type	-0.12	0.20	1.00	0.54	-0.18	0.20	-0.14	0.03
Visibility x Precipitation	-0.09	0.02	0.10	0.26	0.83	-0.39	0.43	0.14
Wind Speed x Precipitation type	0.14	1.00	0.20	0.68	-0.03	0.05	0.08	0.17
Wind Speed x Precipitation	-0.03	0.27	-0.13	0.31	0.77	-0.43	0.56	0.19
Air Temperature x RSI	0.97	0.14	-0.15	0.05	0.03	-0.01	-0.09	0.13
Event duration x RSI	-0.15	0.09	-0.10	0.02	0.39	-0.25	0.95	0.37
Event duration x Precipitation type	-0.19	0.08	-0.14	0.70	0.51	-0.48	1.00	0.35
Event duration x Precipitation	-0.09	0.01	-0.14	0.29	0.90	-0.43	0.63	0.16
Exposure x Visibility	-0.08	0.24	0.95	-0.26	-0.15	0.17	-0.05	0.30
Exposure x RSI	0.21	0.15	0.18	0.14	-0.29	0.74	-0.15	0.60
Exposure x Precipitation type	0.10	0.17	0.03	0.96	0.13	-0.09	0.35	1.00
Exposure x Precipitation	-0.05	-0.02	-0.18	0.35	0.99	-0.47	0.54	0.21

Table 4-6: Correlation Values for Two Way Interaction Terms (HBD Combined Dataset)

2-Way Interaction Variable	Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation type	Hourly Precipitation	RSI	Event Duration (hr)	Exposure
Visibility x Precipitation type	0.01	0.10	0.74	0.54	0.05	0.30	-0.15	0.06
Visibility x Precipitation	0.05	0.03	0.20	0.26	0.62	0.06	-0.07	0.03
Wind Speed x Precipitation type	0.13	0.71	-0.12	0.64	0.21	0.08	0.02	0.08
Wind Speed x Precipitation	0.10	0.35	-0.19	0.31	0.77	-0.08	0.05	0.01
Air Temperature x RSI	0.93	0.12	-0.16	0.05	0.10	-0.12	-0.09	0.18
Exposure x Visibility	-0.06	0.13	0.96	-0.26	-0.23	0.21	-0.12	0.30
Exposure x RSI	0.24	0.05	0.18	0.14	-0.07	0.86	-0.32	0.61
Exposure x Precipitation type	0.16	0.09	-0.24	0.94	0.32	0.20	-0.09	0.31
Exposure x Precipitation	0.11	0.01	-0.23	0.35	0.98	-0.06	-0.01	0.10

Table 4-7: Correlation Values for EBD

	Site ID	Region	Road Type	Monthly ID	Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Ppt. (cm)	RSI	WRM	Event Duration (hr)	Exposure
Site ID	1.00											
Region	-0.56	1.00										
Road Type	-0.81	0.75	1.00									
Monthly ID	0.07	-0.05	-0.06	1.00								
Temperature	0.20	-0.15	-0.20	-0.01	1.00							
Wind Speed	0.16	-0.17	-0.15	0.07	0.14	1.00						
Visibility	0.12	-0.12	-0.04	-0.08	-0.12	0.20	1.00					
Precipitation	-0.09	0.06	0.09	0.00	-0.06	-0.03	-0.18	1.00				
RSI	0.15	-0.16	-0.16	0.04	0.17	0.05	0.20	-0.47	1.00			
WRM	-0.19	0.19	0.19	0.01	-0.20	-0.06	-0.18	0.32	-0.58	1.00		
Event Duration	-0.11	0.13	0.14	0.01	-0.19	0.08	-0.14	0.51	-0.48	0.41	1.00	
Exposure	0.73	-0.43	-0.65	0.07	0.10	0.17	0.03	0.14	-0.09	0.08	0.35	1.00

Table 4-8: Correlation Values for HBD

	Site ID	Region	Road Type	First Hr Effect	Second Hr Effect	Monthly ID	Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Hourly Ppt. (cm)	RSI	WRM	Exposure
Site ID	1.00												
Region	-0.52	1.00											
Road Type	-0.81	0.73	1.00										
First Hr Effect	0.02	-0.03	-0.03	1.00									
Second Hr Effect	0.03	-0.05	-0.05	0.67	1.00								
Monthly ID	0.07	-0.04	-0.06	0.00	-0.01	1.00							
Temperature	0.17	-0.11	-0.17	0.06	0.08	0.01	1.00						
Wind Speed	0.12	-0.12	-0.11	-0.04	-0.06	0.06	0.11	1.00					
Visibility	0.07	-0.07	-0.01	0.04	0.03	-0.06	-0.12	0.09	1.00				
Hourly Ppt	-0.03	-0.02	0.01	0.21	0.18	0.00	0.08	0.00	-0.22	1.00			
RSI	0.14	-0.15	-0.15	0.13	0.20	0.07	0.17	0.03	0.20	-0.10	1.00		
WRM	-0.05	0.09	0.07	-0.01	-0.05	-0.02	0.01	-0.04	-0.10	0.14	-0.22	1.00	
Exposure	0.82	-0.49	-0.76	0.03	0.04	0.09	0.19	0.12	0.06	-0.02	0.19	-0.04	1.00

4.3 Model Development and Calibration

As described in Chapter 2, the most commonly employed approach for modeling accident frequencies is the regression models for count data. In particular, the Negative Binomial (NB) model and its extensions have been found to be the most suitable distribution structures for road accident frequency (Hauer 2001; Shankar et al., 1995; Miaou and Lord 2003; Miranda-Moreno 2006; Sayed and El-Basyouny 2006). Parameters are easy to estimate using maximum likelihood methods. Among the NB model extensions, we can mention the generalized NB, zero inflated NB models, latent-class NB models, etc. (Miaou, 1994; Shankar et al., 1997; Miranda-Moreno, 2006). In this research, the NB model is therefore first evaluated for its performance in capturing observed and unobserved accident variations among individual snow storms. This model can be written as, $Y_i \sim \text{NB}(\mu_i, \alpha)$, where Y_i represents the number of accidents during an event i (i=1,…n), μ_i stands for the mean accident frequency, and α is the over-dispersion parameter. Furthermore, it is assumed that the mean accident frequency (μ_i) is a function of a set of covariates through the log link function commonly used in the road safety literature, that is:

$$\mu_i = \exp(\beta_0 + \beta_1.Ln(Exposure) + \beta_2 x_{i1} + \beta_3 x_{i2} + \cdots + \beta_k x_{ik}) \quad \textbf{(4 - 1)}$$

$$\mu_i = (Exposure)^{\beta_1} \exp(\beta_0 + \beta_2 x_{i1} + \beta_3 x_{i2} + \cdots + \beta_k x_{ik}) \quad \textbf{(4 - 2)}$$

$$\mu_i = (\text{Exposure})^{\beta_1} \times (\text{LengthExposure})^{\beta_1'} \exp(\beta_0 + \beta_2 x_{i1} + \beta_3 x_{i2} + \cdots + \beta_k x_{ik}) \quad \textbf{(4 - 3)}$$

where x_{ij} is the jth attribute associated with event *i*. Exposure terms are as defined in section 4.1 and Chapter 2 and ($\beta_0, \beta_1,\ldots,\beta_k$) is a vector of regression parameters. One of the shortcomings of the NB model is the assumption of a constant over-dispersion parameter (α) for all observations. This assumption can be relaxed by assuming that the dispersion parameter is a function of a set of covariates, using an exponential link function as follows:

$$\alpha_i = \exp(\gamma_0 + \gamma_1 z_{i1} + \gamma_2 z_{i2} + \cdots + \gamma_k z_{im}) \quad \textbf{(4 - 4)}$$

where ($z_{i1},\ldots,z_{im}$) is a vector of event-specific factors that may be different from those explaining μ_i and ($\gamma_0, \gamma_1,\ldots, \gamma_m$) is a vector of parameters associated with the dispersion parameter. The resulting model is commonly referred to as generalized Negative Binomial (GNB) model (Miaou and Lord 2003; Miranda-Moreno et al 2005; Miranda-Moreno 2006). This model may allow more flexibility than its alternatives to deal with the well-known over-dispersion problem and unobserved heterogeneities among events.

The third model structure considered in this research is called Poisson lognormal model (PLN). PLN differs from NB model in the sense that a lognormal distributed error term, instead of gamma distributed error, is added to the Poisson model to capture the unobserved heterogeneity. This model also has the advantage that it can be extended to deal with multi-level datasets. Some statistical software packages such as STATA have built-in functions to extend PLN to a multilevel framework. The multilevel model structure is necessary because the HBD dataset is longitudinal in nature with the hourly records within each storm event forming a set of repeated measures over time, making it different from panel data. The potential within-storm correlation can be captured by a multilevel model (Miranda-Moreno, 2006). Moreover, the Lognormal tails are known to be asymptotically heavier than those of the Gamma distribution (Kim et al, 2002). This can be the case when working with datasets in the presence of outliers (Winkelmann, 2003).

In a multilevel setting, a Poisson/Lognormal model for nested hourly observations at the event level can be represented as,

$$Y_{im} \sim \text{Poisson}\ (\theta_{im}),\ \text{with}\ \ln(\theta_{im}) = \mu_{im} + \gamma_m + \varepsilon_{im} \qquad \textbf{(4 - 5)}$$

where, θ_{im} and μ_{im} are defined as the number and mean number of accidents in hour i over storm event m; γ_m represents an event level random effect, following a Normal distribution, i.e., $\gamma_m \sim N(0, \tau)$; ε_{im} is the model error following normal distribution, i.e., $\varepsilon_{im} \sim N(0, \zeta)$. Note that ε_{im} represents all the unobserved heterogeneities or random variations that are not captured by γ_m, where, γ_m represents event-level unobserved factors controlling for the potential within-event correlation. In this case, the equation for the mean accident frequency has the following functional form:

$$\mu_{im} = (Exposure_m)^{\beta_1} \exp(\beta_0 + \beta_2 x_{i1m} + \beta_3 x_{i2m} + \cdots + \beta_k x_{ikm}) \exp^{\tau/2} \qquad \textbf{(4 - 6)}$$

Where, m is an index indicating the event level and i the hour index. It should be noted that the random term in **Equation 4 - 6** only considers the random effect on the intercept. A more complex extension would consider the random effects in the slopes, that is, the slopes could be assumed to vary by events. This variation is left for future investigation.

After identifying the modelling approaches, the next step was to fit the models to the data. Though models were calibrated for all the 64 data sets, only EBD and HBD will be discussed here because of their relatively large sample size and varied nature which makes it feasible to check the effects of different site specific factors. Results obtained with large sample sizes are most trustworthy (Wright 1995). In general results obtained with individual sites were consistent. For each dataset two functional forms (**Equation 4 – 2** and **4 – 3**) were tested under different scenarios. Following **Equation 3 – 3**, different relationships of RSI to the mean number of accidents were tested and it was found that the models fit is improved when RSI is used in a linear fashion (with $\alpha_2 = 1$ from **Equation 3 – 3**). This is explained in **Section 4.3.5**.

The following types of models were calibrated for EBD:

A. Negative Binomial[4]

- EBD-NB1: A model without any spatial factors and combined exposure measure
- EBD-NB2: A model without any spatial factors and separate exposure measures
- EBD-NB3: A model with regional effects and combined exposure measure
- EBD-NB4: A model with regional effects and separate exposure measures
- EBD-NB5: A model with road type effects and combined exposure measure
- EBD-NB6: A model with road type effects and separate exposure measures
- EBD-NB7: A model with site effects and combined exposure measure
- EBD-NB8: A model with site effects and separate exposure measures

B. Generalised Negative Binomial

- EBD-GNB1: A model without any spatial factors and combined exposure measure
- EBD-GNB2: A model without any spatial factors and separate exposure measures
- EBD-GNB3: A model with regional effects and combined exposure measure
- EBD-GNB4: A model with regional effects and separate exposure measures
- EBD-GNB5: A model with road type effects and combined exposure measure

[4] See Appendix M for these results

- EBD-GNB6: A model with road type effects and separate exposure measures
- EBD-GNB7: A model with site effects and combined exposure measure
- EBD-GNB8: A model with site effects and separate exposure measures

PLN was also calibrated and compared with the best fit model from the above to check its power for explaining accident variation. Results showed that PLN has a very good fit to the model comparable to the best fit model (GNB 7) and parameter estimates were consistent with the general findings from other model structures.

HBD is a 2-level hierarchical dataset where storm hours are nested within a storm. As described in Chapter 2, this type of data generally suffers from within subject correlation. Intra-class correlation (ICC) (correlation among observations within the same storm event) was computed for this correlation as described in Chapter 2. ICC, denoted by ρ, has a value ranging from 0 to 1. This means that if all hourly accident count observations are independent of one another, then $\rho = 0$. On the other hand, if observations inside each cluster (in this case, storm) are exactly the same, $\rho = 1$. Obviously, a $\rho \neq 0$ implies that the observations are not independent, e.g., ICC > 0 implies that the accident occurrence in the same storm is influenced by similar unobserved storm factors. Using Equation 2 – 31, ICC for this dataset (HBD) comes out to be 6.05%. Though there is no set rule for the ICC value; a value close to zero suggests the presence of weak correlation. Under such circumstances the less complex single level models could also be applied to this data. In such cases the distortion effect of the correlation on the parameter estimate is expected to be minimal.

From the above modeling results it was found that in general models with a single combined exposure measure has almost the same performance as those with two separate measures. As a result, in the subsequent analysis on HBD, we consider only the combined exposure term. The following models were calibrated for HBD.

A. Poisson lognormal - Two Level Models

- HBD-PLN1: A model without any spatial factors
- HBD-PLN 2: A model with regional effects
- HBD-PLN 3: A model with road type effects
- HBD-PLN 4: A model with site effects

B. Generalised Negative Binomial - Single Level Models

- HBD-GNB1: A model without any spatial factors
- HBD-GNB2: A model with regional effects
- HBD-GNB3: A model with road type effects
- HBD-GNB4: A model with site effects

HBD-GNB models were calibrated treating HBD data as single level, ignoring the correlation whereas PLN models were calibrated using the 2-level hierarchical structure of the HBD data. PLN modeling results for individual sites are given in Appendix – N.

4.3.1 Modeling Results

All models were calibrated using STATA[5] (Version 11). A stepwise elimination process was followed to identify the significant factors. **Table 4 – 9** show EBD results from GNB (and PLN model applied with the same settings as EBD – GNB7) models. AIC was used to identify the best fit model. As shown in **Table 4 – 9**, the calibration results are quite consistent in terms of significant factors and coefficients across the models. **Table 4 – 10** show HBD modeling results for GNB and PLN.

[5] http://www.stata.com/

Table 4-9: Summary Results of GNB (with PLN) Model from EBD Analysis

Variable	EBD - GNB1		EBD - GNB2		EBD - GNB3		EBD-GNB4		EBD-GNB5		EBD-GNB6		EBD-GNB7		EBD-GNB8		EBD-PLN Model	
	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-7.478	0.000	-7.306	0.000	-6.296	0.000	-6.902	0.000	-5.351	0.000	-5.393	0.000	-3.912	0.000	26.041	0.000	-4.653	0.000
October	0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
November	-0.994	0.000	-1.006	0.000	-1.108	0.000	-1.084	0.000	-1.008	0.000	-1.006	0.000	-1.048	0.000	-1.048	0.000	-1.108	0.000
December	-1.153	0.000	-1.165	0.000	-1.276	0.000	-1.256	0.000	-1.179	0.000	-1.177	0.000	-1.229	0.000	-1.229	0.000	-1.180	0.000
January	-1.076	0.000	-1.089	0.000	-1.211	0.000	-1.191	0.000	-1.099	0.000	-1.096	0.000	-1.193	0.000	-1.193	0.000	-1.119	0.000
February	-1.423	0.000	-1.435	0.000	-1.558	0.000	-1.546	0.000	-1.451	0.000	-1.449	0.000	-1.537	0.000	-1.537	0.000	-1.496	0.000
March	-1.156	0.000	-1.167	0.000	-1.290	0.000	-1.276	0.000	-1.174	0.000	-1.172	0.000	-1.248	0.000	-1.248	0.000	-1.218	0.000
April	-0.925	0.001	-0.934	0.001	-1.047	0.000	-1.039	0.000	-0.940	0.001	-0.939	0.001	-1.049	0.000	-1.049	0.000	-1.013	0.000
Temperature									-0.009	0.177	-0.009	0.179	-0.018	0.007	-0.018	0.007		
Wind Speed	0.008	0.009	0.008	0.012	0.005	0.092	0.007	0.043	0.009	0.006	0.009	0.006	0.009	0.003	0.009	0.003	0.009	0.003
visibility	-0.034	0.000	-0.034	0.000	-0.039	0.000	-0.040	0.000	-0.032	0.000	-0.032	0.000	-0.044	0.000	-0.044	0.000	-0.045	0.000
Total Precipitation									0.013	0.000	0.013	0.000	0.014	0.000	0.014	0.000		
RSI	-4.487	0.000	-4.503	0.000	-4.593	0.000	-4.595	0.000	-4.482	0.000	-4.486	0.000	-4.420	0.000	-4.421	0.000	-4.862	0.000
Ln(Exposure)	0.822	0.000			0.768	0.000			0.699	0.000			0.648	0.000			0.709	0.000
Traffic Exposure			0.819	0.000			0.758	0.000			0.697	0.000			0.648	0.000		
Length Exposure			0.791	0.000			0.969	0.000			0.716	0.000			-8.345	0.000		
RDTYPE1									0.000		0.000							
RDTYPE2									-1.043	0.000	-1.049	0.000						
RDTYPE3									-0.808	0.000	-0.802	0.000						
RDTYPE4									-0.452	0.000	-0.459	0.000						
RDTYPE5									-0.541	0.000	-0.562	0.000						
RDTYPE6									-1.182	0.000	-1.187	0.000						
RDTYPE7									-1.310	0.000	-1.324	0.000						
RDTYPE8									-0.886	0.000	-0.909	0.000						

Table 4 – 9: Cont.

Variable	EBD - GNB1		EBD - GNB2		EBD - GNB3		EBD-GNB4		EBD-GNB5		EBD-GNB6		EBD-GNB7		EBD-GNB8		EBD-PLN Model	
	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Region1					0.000		0.000											
Region2					-0.497	0.000	-0.674	0.000										
Region3					-0.316	0.009	-0.444	0.000										
Region4					-0.492	0.003	-0.755	0.000										
Region5					-0.053	0.506	-0.269	0.009										
Sioux Narrows													-2.607	0.000	9.622	0.000	-2.375	0.000
Elliot Lake													-1.232	0.021	2.721	0.000	-0.840	0.093
Grand Bend													-2.815	0.000	3.837	0.000	-2.733	0.000
Carleton													-3.317	0.000	-4.218	0.000	-3.265	0.000
Shabauqua													-2.464	0.000	-0.216	0.715	-2.208	0.000
Cochrane													-1.936	0.000	6.066	0.000	-1.665	0.000
North Bay													-1.456	0.000	3.938	0.000	-1.238	0.000
Massey													-1.268	0.000	5.567	0.000	-1.076	0.000
Nipigon													-2.181	0.000	9.690	0.000	-2.054	0.000
Port Severn													-2.128	0.000	3.713	0.000	-1.980	0.000
Graven Hurst													-1.782	0.000	1.093	0.001	-1.648	0.000
Kenora													-1.374	0.000	10.581	0.000	-1.227	0.000
Kaladar													-1.287	0.000	10.042	0.000	-1.164	0.000
Snelgrove													-2.139	0.000	-1.869	0.000	-2.072	0.000
Simcoe													-1.497	0.000	12.978	0.000	-1.479	0.000
Shelburne													-2.019	0.000	4.904	0.000	-1.941	0.000
Morrisburg													-1.467	0.000	10.580	0.000	-1.405	0.000
QEW 2													-1.410	0.000	-0.689	0.000	-1.465	0.000
Highway 410													-1.631	0.000	-8.560	0.000	-1.628	0.000
Dunvegan													-1.459	0.000	11.221	0.000	-1.415	0.000
Port Hope													-0.628	0.000	8.633	0.000	-0.668	0.000
Patrol 5													-1.384	0.000	-8.219	0.000	-1.372	0.000

Table 4 – 9: Cont.

Variable	EBD - GNB1		EBD - GNB2		EBD - GNB3		EBD-GNB4		EBD-GNB5		EBD-GNB6		EBD-GNB7		EBD-GNB8		EBD-PLN Model	
	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
QEW 1													-1.143	0.000	-3.839	0.000	-1.150	0.000
Patrol 4													-0.997	0.000	-5.228	0.000	-0.975	0.000
Kanata Patrol													-1.635	0.000	1.691	0.000	-1.611	0.000
Woodstock													-0.810	0.000	7.730	0.000	-0.809	0.000
Patrol 1													-1.175	0.000	0.169	0.265	-1.237	0.000
Hwy 404													-1.606	0.000	0.998	0.000	-1.660	0.000
Maple													-1.216	0.000	1.933	0.000	-1.289	0.000
Patrol 3													-0.986	0.000	0.000		-1.070	0.000
Patrol 2													0.000		0.000		0.000	
Ln(Alpha)																		
Constant	8.780	0.000	8.780	0.000	8.733	0.000	8.533	0.000	4.388	0.000	4.371	0.000	4.133	0.000	4.130	0.000		
Ln(Exposure)	-0.574	0.000	-0.575	0.000	-0.578	0.000	-0.563	0.000	-0.331	0.000	-0.329	0.000	-0.335	0.000	-0.335	0.000		
Visibility									0.034	0.012	0.034	0.012	0.039	0.011	0.039	0.011		
RDTYPE1	0.000				0.000		0.000											
RDTYPE2	0.179	0.503	0.197	0.461	0.366	0.165	0.395	0.128										
RDTYPE3	-0.549	0.010	-0.534	0.013	-0.614	0.007	-0.687	0.003										
RDTYPE4	-0.422	0.024	-0.405	0.032	-0.334	0.079	-0.398	0.041										
RDTYPE5	-1.313	0.000	-1.303	0.000	-1.362	0.000	-1.340	0.000										
RDTYPE6	-0.997	0.039	-0.970	0.044	-0.826	0.079	-0.839	0.077										
RDTYPE7	-0.182	0.712	-0.179	0.717	0.146	0.752	0.037	0.939										
RDTYPE8	-1.472	0.000	-1.477	0.000	-1.324	0.000	-1.273	0.001										
Observations	10932		10932		10932		10932		10932		10932		10932		10932		10932	
LL(Null)	-6079.783		-6079.783		-6079.783		-6079.783		-6095.807		-6095.807		-6095.807		-6108.696			
LL(Model)	-5055.772		-5055.955		-5034.113		-5029.049		-4977.093		-4977.58		-4834.802		-4850.907		-4852.114	
AIC	10151.54		10153.91		10116.23		10108.1		10000.19		10003.16		9761.604		9787.814		9788.229	

Table 4-10: Summary Results of GNB and PLN Models from HBD Analysis

Variable	HBD-GNB1		HBD-PLN1		HBD-GNB2		HBD-PLN2		HBD-GNB3		HBD-PLN3		HBD-GNB4		HBD-PLN4	
	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-8.246	0.000	-8.811	0.000	-5.729	0.000	-6.675	0.000	-3.940	0.000	-4.870	0.000	-1.249	0.006	-2.082	0.000
October	0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
November	-0.761	0.003	-0.772	0.004	-1.111	0.000	-1.106	0.000	-0.934	0.000	-0.863	0.001	-1.029	0.000	-1.023	0.000
December	-0.927	0.000	-0.869	0.001	-1.331	0.000	-1.225	0.000	-1.122	0.000	-1.107	0.000	-1.262	0.000	-1.174	0.000
January	-0.898	0.000	-0.830	0.001	-1.369	0.000	-1.261	0.000	-1.100	0.000	-1.062	0.000	-1.308	0.000	-1.238	0.000
February	-1.217	0.000	-1.135	0.000	-1.637	0.000	-1.527	0.000	-1.382	0.000	-1.355	0.000	-1.536	0.000	-1.488	0.000
March	-0.952	0.000	-0.958	0.000	-1.373	0.000	-1.263	0.000	-1.113	0.000	-1.122	0.000	-1.278	0.000	-1.229	0.000
April	-0.729	0.005	-0.666	0.016	-1.125	0.000	-1.005	0.000	-0.912	0.000	-0.833	0.002	-1.134	0.000	-1.050	0.000
First hour (FH=1)	-0.285	0.001	-0.262	0.001	-0.271	0.002	-0.256	0.002	-0.313	0.000	-0.285	0.001	-0.302	0.001	-0.271	0.001
Other Wise (FH=0)	0.000				0.000		0.000		0.000		0.000		0.000		0.000	
Temperature					-0.012	0.009	-0.014	0.005					-0.011	0.021	-0.013	0.014
Wind Speed (Km/hr)	0.007	0.000	0.008	0.000	0.004	0.040	0.006	0.006	0.006	0.002	0.008	0.000	0.005	0.017	0.006	0.003
visibility (km)	-0.035	0.000	-0.033	0.000	-0.042	0.000	-0.038	0.000	-0.033	0.000	-0.033	0.000	-0.039	0.000	-0.038	0.000
Hourly Precipitation									0.082	0.140			0.097	0.079		
RSI	-2.763	0.000	-2.558	0.000	-2.667	0.000	-2.516	0.000	-2.728	0.000	-2.580	0.000	-2.594	0.000	-2.518	0.000
Ln(Exposure)	0.718	0.000	0.705	0.000	0.551	0.000	0.569	0.000	0.412	0.000	0.448	0.000	0.235	0.000	0.276	0.000
RDTYPE1									0.000		0.000					
RDTYPE2									-0.922	0.000	-0.937	0.000				
RDTYPE3									-1.049	0.000	-1.071	0.000				
RDTYPE4									-0.563	0.000	-0.596	0.000				
RDTYPE5									-0.820	0.000	-0.811	0.000				
RDTYPE6									-1.716	0.000	-1.617	0.000				
RDTYPE7									-1.738	0.000	-1.688	0.000				
RDTYPE8									-1.767	0.000	-1.671	0.000				

Table 4 – 10: Cont.

Variable	HBD-GNB1		HBD-PLN1		HBD-GNB2		HBD-PLN2		HBD-GNB3		HBD-PLN3		HBD-GNB4		HBD-PLN4	
	B	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	Sig	B	Sig
Region1					0.000		0.000									
Region2					-0.696	0.000	-0.586	0.000								
Region3					-0.922	0.000	-0.777	0.000								
Region4					-1.166	0.000	-1.027	0.000								
Region5					-0.340	0.000	-0.323	0.000								
Sioux Narrows													-4.027	0.000	-3.904	0.000
Elliot Lake													-3.522	0.000	-3.276	0.000
Grand Bend													-4.011	0.000	-3.924	0.000
Carleton													-3.875	0.000	-3.847	0.000
Shabauqua													-4.010	0.000	-3.874	0.000
Cochrane													-3.399	0.000	-3.293	0.000
North Bay													-2.853	0.000	-2.723	0.000
Massey													-2.370	0.000	-2.252	0.000
Nipigon													-3.090	0.000	-3.001	0.000
Port Severn													-3.001	0.000	-2.886	0.000
Graven Hurst													-2.483	0.000	-2.396	0.000
Kenora													-2.518	0.000	-2.425	0.000
Kaladar													-2.388	0.000	-2.289	0.000
Snelgrove													-2.788	0.000	-2.732	0.000
Simcoe													-2.196	0.000	-2.155	0.000
Shelburne													-2.595	0.000	-2.557	0.000
Morrisburg													-1.727	0.000	-1.688	0.000
QEW 2													-1.580	0.000	-1.671	0.000
Highway 410													-1.995	0.000	-2.055	0.000
Dunvegan													-1.709	0.000	-1.650	0.000
Port Hope													-0.732	0.000	-0.797	0.000

Table 4 – 10: Cont.

Variable	HBD-GNB1		HBD-PLN1		HBD-GNB2		HBD-PLN2		HBD-GNB3		HBD-PLN3		HBD-GNB4		HBD-PLN4	
	B	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	**Sig**	**B**	Sig	B	Sig
Patrol 5													-1.747	0.000	-1.770	0.000
QEW 1													-1.297	0.000	-1.375	0.000
Patrol 4													-1.315	0.000	-1.288	0.000
Kanata Patrol													-1.605	0.000	-1.619	0.000
Woodstock													-0.969	0.000	-0.978	0.000
Patrol 1													-1.038	0.000	-1.157	0.000
Hwy 404													-1.298	0.000	-1.384	0.000
Maple													-1.074	0.000	-1.140	0.000
Patrol 3													-0.710	0.000	-0.789	0.000
Patrol 2													0.000		0.000	
Ln(Alpha)																
Constant	3.828	0.000			4.146	0.000			2.932	0.010			2.711	0.012		
RSI	1.692	0.000			1.537	0.000			1.487	0.000			1.347	0.000		
Ln(Exposure)	-0.301	0.001			-0.327	0.000			-0.231	0.024			-0.222	0.022		
Observations	122058		122058		122058		122058		122058		122058		122058		122058	
LL(Null)	-13095.64				-13095.64				-13095.64				-13095.64			
LL(Model)	-12118		-12036.25		-12036.94		-11990.92		-11877.64		-11885.65		-11647.45		-11716.16	
AIC	24265.99		24098.51		24113.89		24017.84		23801.29		23811.29		23388.91		23520.31	
BIC	24411.68		24224.77		24308.13		24192.66		24024.67		24017.25		23845.38		23947.65	
Number of level 1 units			122058				122058				122058				122058	
Number of level 2 units			10932				10932				10932				10932	

4.3.2 Comparison of Models

The calibrated models described in the previous section are first compared using the goodness-of-fit statistic – AIC, as described in Chapter 2. The AIC values of these models are shown in **Figure 4 – 1** and **Figure 4 – 2** for EBD and HBD.

In addition to using AIC for best fit model, we also compared the observed versus the estimated relative frequencies of the number of accidents (Maher and Summersgill, 1996; Miranda-Moreno 2006) for EBD-GNB7 (**Figure 4 - 3**), and HBD-GNB4 & HBD-PLN4 (**Figure 4 - 4**). **Figure 4 – 4** shows that HBD – GNG4 estimates are more close to the observed once.

Based on the AIC value, EBD-GNB7 model was selected as the best fit model to the data for EBD and HBD-GNB4 for HBD.

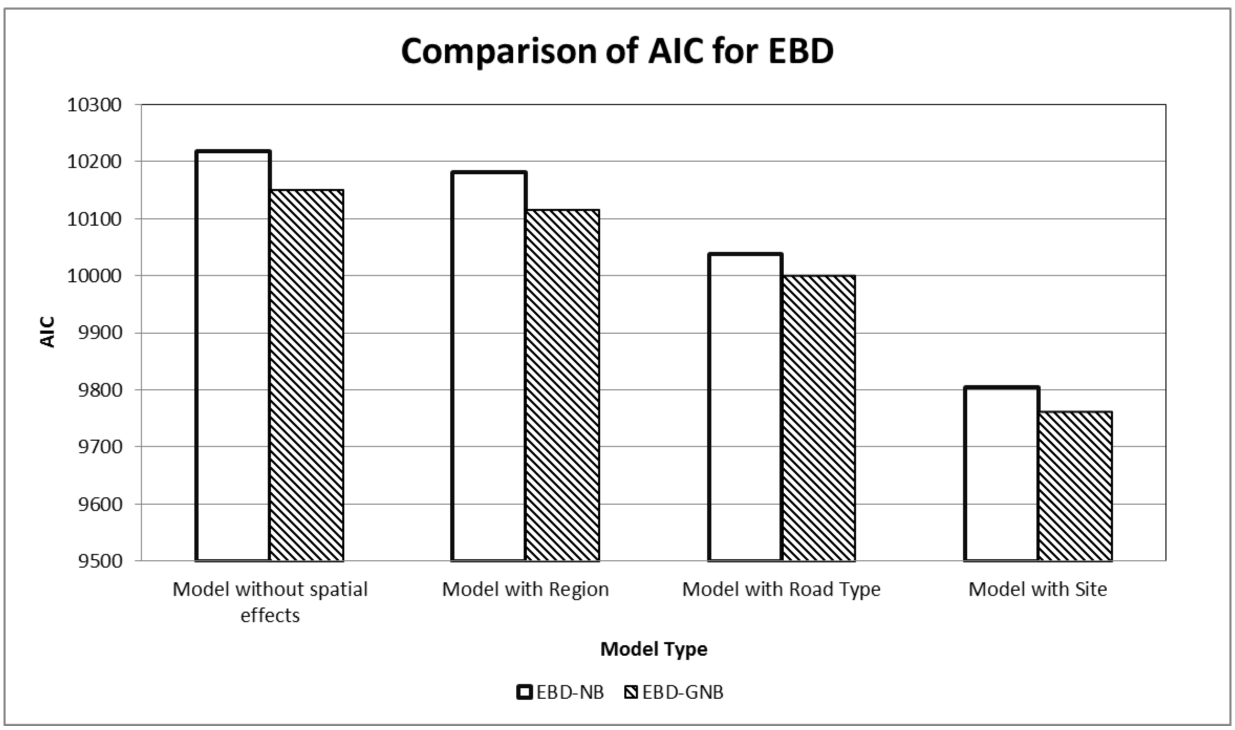

Figure 4-1: AIC comparison for EBD

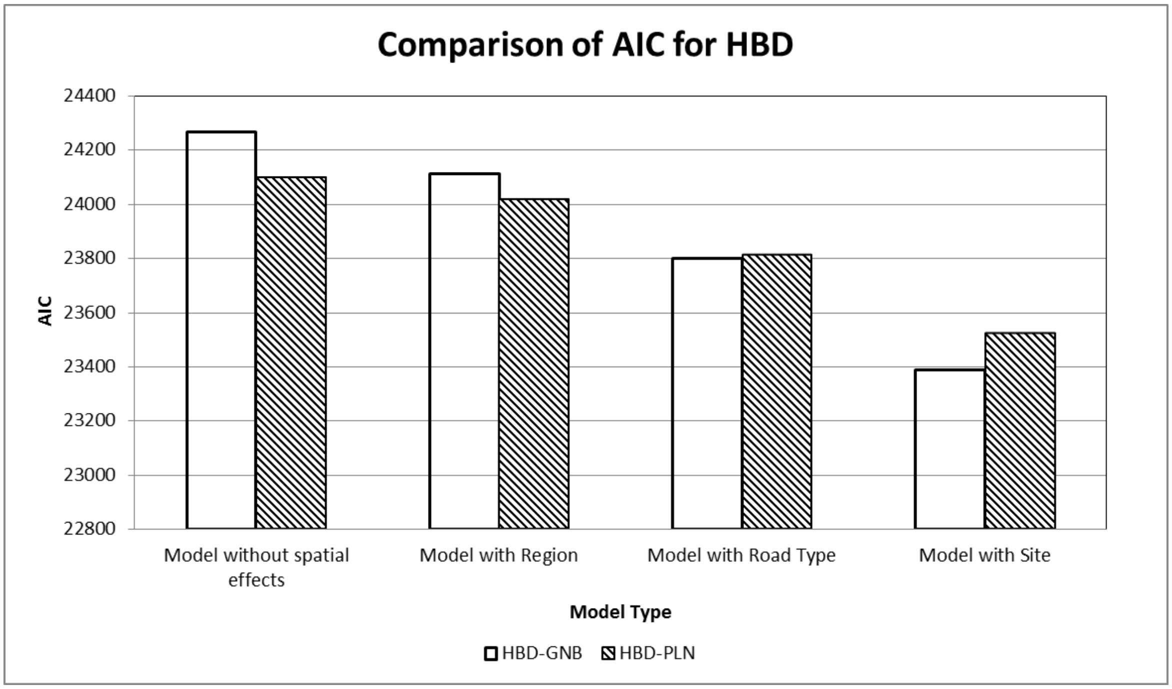

Figure 4-2: AIC comparison for HBD

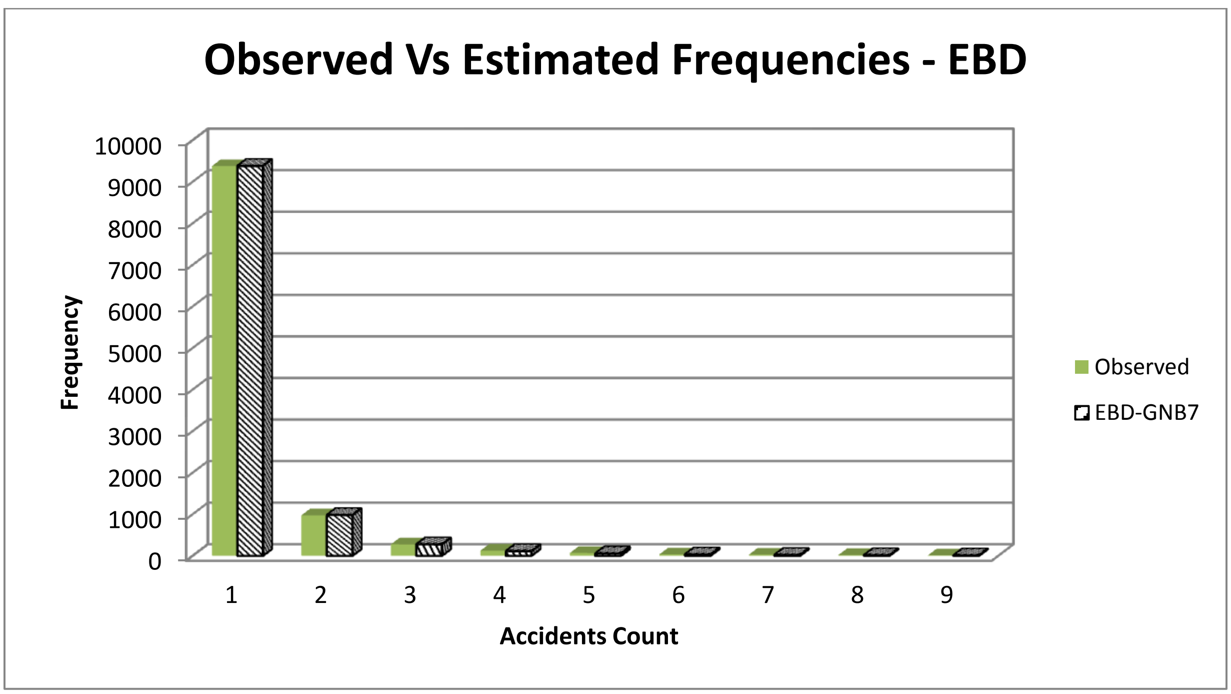

Figure 4-3: Observed vs. estimated accident frequencies - EBD

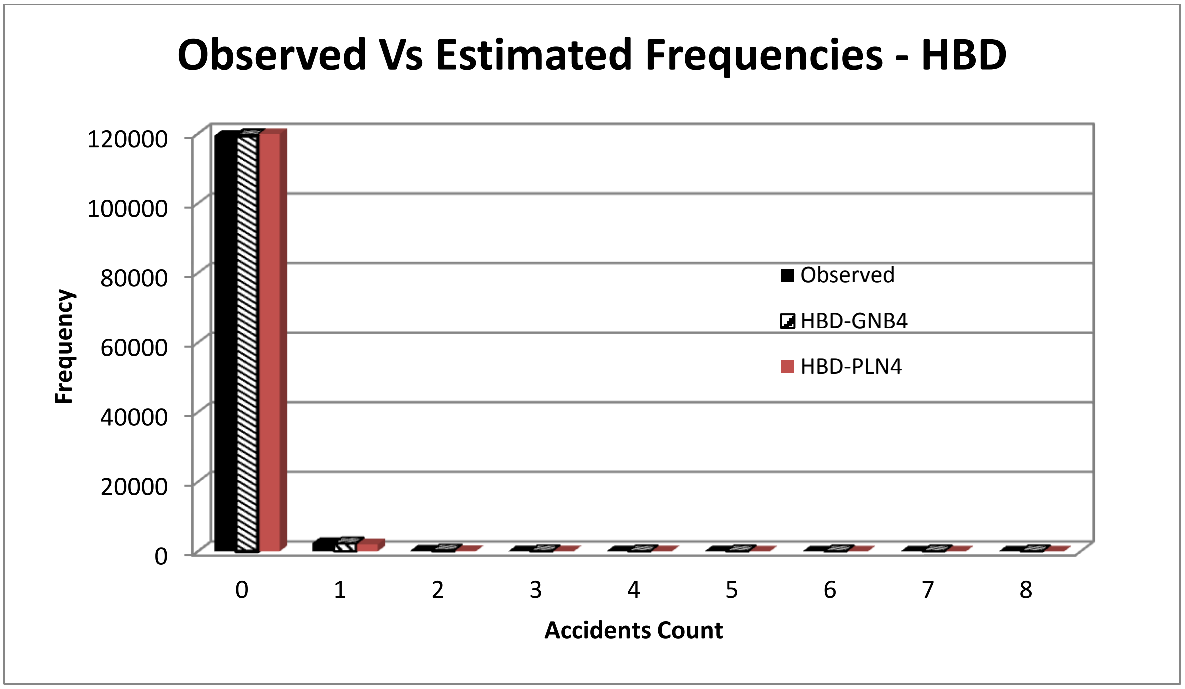

Figure 4-4: Observed vs. estimated accident frequencies - HBD

4.3.3 Effects of Site/Highway Characteristics

It is not possible to account for all the factors affecting collision frequency in a model. Spatial variables were included to capture possible effects of other route specific factors, such as location, driver population, and road geometry, on road safety. **Figure 4 – 1** and **Figure 4 – 2** shows a consistent trend regarding the addition of spatial variables to the models. Models with spatial variables show better fit than models without any spatial variables. The more the spatial variables represent the sites, the more the model fit improves. The models with variables representing road type had a better fit than those with regional level variables while the models with site specific factors had a better fit than those with road type specific factors. This may be due to the additional variation in collisions explained by the disaggregate spatial variables than the aggregate ones.

Figure 4 – 2 shows that for models without spatial features or with spatial features at an aggregate level (i.e., by region), two level models (HBD-PLN) have better fit than single level models (HBD-GNB). However with the addition of spatial variables at a disaggregate level such as road type or the individual site itself, single level models perform better.

Site specific factors could also be modeled as a function of other variables related to site (e.g. number of vehicles in the area, number of lanes, speed limit, number of interchanges, number of curves etc.), weather (e.g. total precipitation intensity; average values for temperature, visibility, wind speed at some temporal aggregation level etc.), and traffic volume. This approach could be used to generalize the frequency models developed to other road jurisdictions. This assumption is however not tested here and is left for future investigation.

4.3.4 Effects of Data Aggregation and Correlation

Use of aggregated data (e.g. annual or monthly basis) is common in road safety literature either to avoid the correlation within the data by averaging it or due to the unavailability of data at a disaggregate level. This aggregation, although it takes care of the correlation in the data, results in a loss of information. For instance, when investigating the impact of weather (precipitation and temperature) and winter maintenance operations on safety, the variations of weather variables over short periods of time (hours or days) is likely to be highly influential in generating crashes. Moreover, at a disaggregate level the variables are more representative of the conditions at the time of collision than at a disaggregate level. In this research we have used datasets aggregated at two levels: EBD and HBD. Different methodologies were used to analyze these datasets. For EBD single level models (NB and GNB) were used whereas for HBD single level (GNB) and 2-level (PLN) models were used. In this section we evaluate the effects of data aggregation and correlation on the modeling outcome. Results from EBD and HBD models are used for the effects of data aggregation whereas results from single level and 2-level models from HBD are used to show the effects of data correlation.

All the models have consistent results in terms of the effects of parameter estimates when dealing with the same data. **Table 4 – 11** shows the percent change in parameter estimate for EBD-GNB7 and HBD-PLN4 using HBD-GNB4 as the base model. A positive sign means a higher parameter estimate for HBD-GNB4 than EBD-GNB7 and HBD-PLN4. Changes in parameter estimates for single and multilevel HBD models are quite reasonable. This might be due to the fact that correlation within events is not that strong for accidents (Goldstein, 1986). The difference is, however, noticeable between EBD and HBD. This difference is caused by the effects of data aggregation. The negative sign shows that the effect size of a parameter is greater for EBD – GNB7 than for HBD – GNB4. For example, the coefficient associated with RSI changed from -2.594 in HBD – GNB4 to -4.42 in EBD – GNB7, a 70% increase in effect size. Graphically this has been shown in **Figure 4 – 5** to **Figure 4 – 8** for exposure, RSI, visibility and wind speed respectively. In this research sample sizes for both EBD and HBD were large. However, for cases with small sample sizes, data aggregation could result in turning some of the variables insignificant due to loss of information by data aggregation.

Despite these differences in model parameter estimates, in general, both models have their own advantages. For example, EBD model would be a suitable candidate under situations where detailed hourly data is not available or when the objective is the performance evaluation of different patrol routes. HBD model on the other hand is more suitable for sites with detailed data and evaluation of performance of different WRM strategies for the same patrol route. This has been discussed in section 4.4.

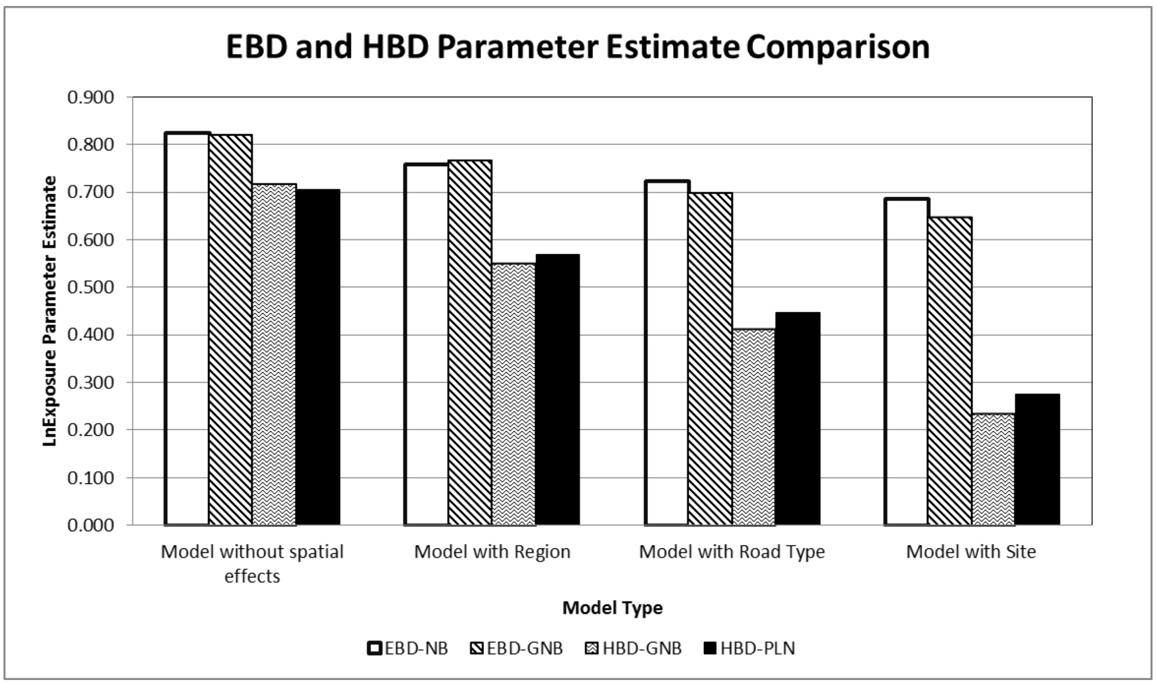

Figure 4-5: Exposure parameter estimate comparison for EBD and HBD models

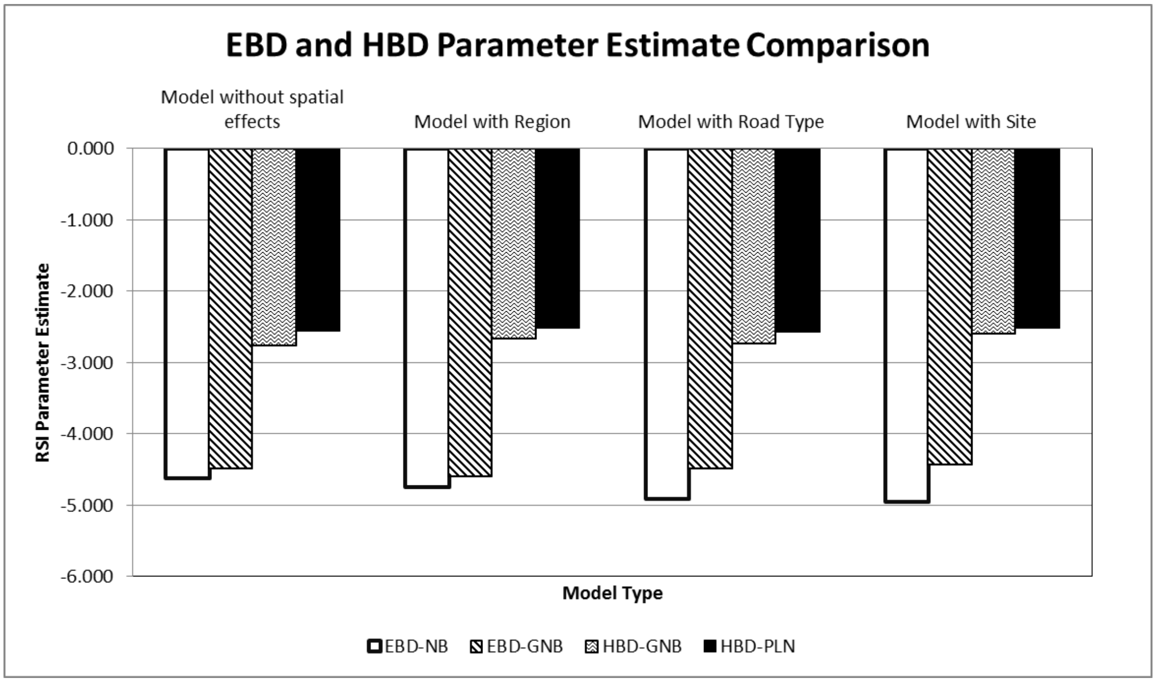

Figure 4-6: RSI parameter estimate comparison for EBD and HBD models

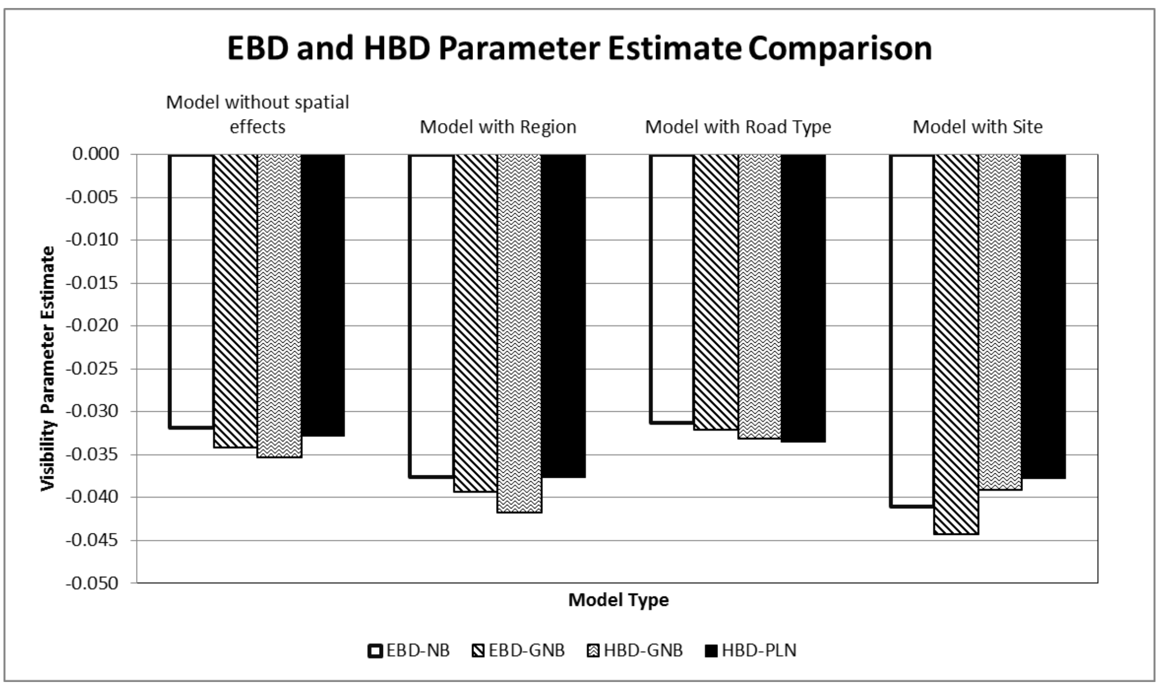

Figure 4-7: Visibility parameter estimate comparison for EBD and HBD models

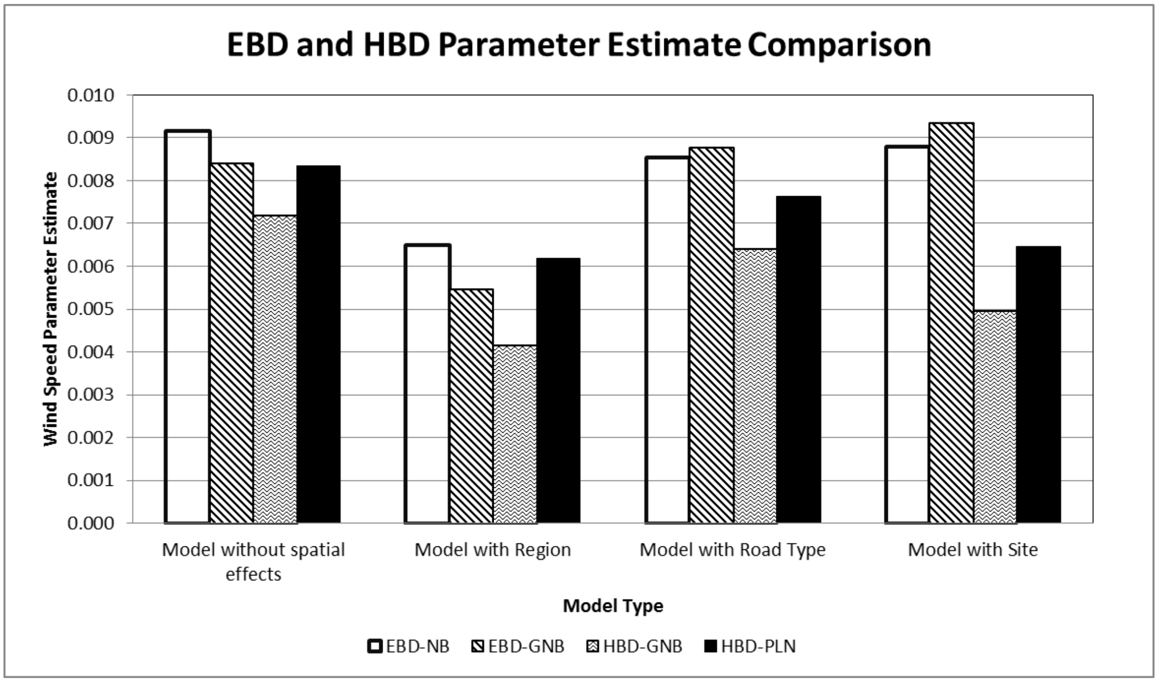

Figure 4-8: Wind Speed parameter estimate comparison for EBD and HBD models

Table 4-11: Elasticities and Percent Change in Parameter Estimate

Variable	Change in parameter estimate between HBD-GNB4 & HBD-PLN4	Elasticities HBD-GNB4	Change in parameter estimate between HBD-GNB4 & EBD-GNB7	Elasticities EBD-GNB7
Temperature	-16%	0.06%	-62%	0.08%
Wind Speed (Km/hr)	-31%	0.08%	-89%	0.15%
visibility (km)	3%	-0.44%	-13%	-0.52%
Hourly Precipitation (Total for EBD)		0.02%		0.06%
RSI	3%	-1.93%	-70%	-3.54%
Ln(Exposure)	-17%	0.235%	-176%	0.684%

Both the models show a similar pattern of sensitivities with exposure and RSI as the more pronounced factors affecting accident risk.

4.3.5 Model Interpretation

Most results obtained in our research with respect to winter road safety and associated factors are consistent with those reported in the literature, with a few exceptions. Because of the exponential functional form, the exponent in the model is a measure of sensitivity of crash frequency to the corresponding variable. For example, the coefficient associated with RSI in the HBD-GNB4 is -2.594, which suggests that a 1% improvement in RSI would lead to approximately a 2.59RSI% reduction in the expected number of accidents. If the mean value of RSI (0.7457) from HBD is used as the base value for RSI, then a 1% increase in RSI will result in 1.93% (2.594*0.7457) reduction in mean number of crashes. **Table 4 – 11** provides elasticities for HBD – GNB4 and EBD – GNB7. In the following section elasticities for HBD – GNB4 are discussed only. Temperature, visibility, wind speed and precipitation in the models represent the severity of snow storm events and show that the more severe the snow storm is, the higher will be the expected number of collisions. The following specific observations could be made from the modeling outcomes for EBD-GNB7 and HBD-GNB4:

- **Road Surface Index (RSI)**

  The most interesting result is perhaps that the road surface condition index (RSI) was found to be a statistically significant factor influencing road safety across all sites, models and functional forms. This term was used as a surrogate measure to capture the effects of winter road maintenance operations. The negative sign associated to the factor suggests that higher accident frequencies are associated with poor road surface conditions. This result makes intuitive sense and has confirmed the findings of many past studies (Norrman et al 2000; Wallman et al 1997), mostly from Nordic countries. However, this research is the first showing the empirical relationship between safety and road surface conditions at a disaggregate level, making it feasible to quantify the safety benefit of alternative maintenance goals and methods. Based on Equation 3 – 3, different values of α_2 were used. For $\alpha_2 = 1$, AIC value was 23388.95 where as for $\alpha_2 = -1$ and 2 the AIC values are 23617.94 and 23426.38 respectively from HBD – GNB4 models. This shows that model with RSI included in a linear form improves model fir. The elasticity value for RSI shows that it is most influential factor affecting safety and a 1% improvement in road surface conditions will cause a reduction in mean number of accidents for HBD by almost 2%.

- **Visibility (Km)**

  Visibility is also found to have a statistically significant effect on accident frequency during a snow storm. The negative model coefficient also makes intuitive sense, as it suggests that reduced visibility was associated with an increased number of accidents. Note that this result is different from those from a past study by Hermans et al. (2006a), which conducted a statistical study using data from 37 sites and found that visibility was significant only at two sites. Their study considered collisions occurring at different roadways related to a single weather station. This approach may have masked the effect of visibility due to confounding of missing factors and large aggregation levels in both space (coastal areas vs. inter cities) and time (seasonal variation). The elasticity value for visibility shows that, out of all the weather related factors, it is the most influential factor affecting winter road safety. An increase of 1% in visibility will result in almost a half percent reduction in the mean number of accidents.

- **Exposure**

  As expected, exposure, defined as million vehicle-kilometres traveled (product of the total traffic volume over a storm event and route length for aggregate data and product of the traffic volume per hour and route length for disaggregate data), was found to be significant, suggesting that an increase in traffic volume, storm duration, or route length would lead to an increase in the total number of accidents that would be expected to occur on the route over the snow event. Inclusion of this term ensures that traffic exposure is accounted for when estimating the safety benefits of some specific policy alternatives. The coefficient associated with the exposure term has a value less than one, suggesting that the moderating effect of exposure is non-linear with a decreasing rate. This result is consistent with those from road safety literature (e.g. Andrew and Barred 1998, Lord and Persaud 2000; NCHRP 2001; Roozenburg and Turner 2005; Mustakim et al 2006, Sayed and El-Basyouny 2006; Sayed and Lovegrove 2007, Jonsson et al 2007 and Lord et al 2008 etc.). Exposure also has a great impact on safety and an increase in either length or traffic volume causing the exposure to increase by 1% will cause the mean number of accidents to increase by 0.235%.

- **Precipitation Intensity (cm)**

  Precipitation (total for EBD and hourly for HBD) was also found to be significant with a positive sign suggesting that the mean number of accidents will increase with an increase in precipitation intensity. This finding also confirms some previous results e.g. Knapp et al (2000), Andrey et al (2001), Fu et al (2006) etc. The elasticity value for precipitation shows that a 1% increase in precipitation intensity will cause the mean number of accidents to increase by 0.02%.

- **Air Temperature (C^o)**

  Air temperature was found to be significant with a negative sign suggesting that the mean number of accidents will increase as temperature starts decreasing. Moreover temperature also accounts for extra variation that is not captured by RSI. For the same RSI, different temperatures will represent different levels of variation in road surface conditions which will increase with decrease in temperature. A low temperature will therefore also affect expected accident frequency by offering extra variation in the road surface conditions. This result confirms some of the previous findings e.g. Fu et al. (2006). The elasticity value for air temperature shows that a 1% increase in precipitation intensity will cause the mean number of accidents to increase by 0.06%.

- **Wind Speed (Km/hr)**

  Wind speed was found to be statistically significant and the positive sign indicates that higher wind speeds were associated with a higher number of accidents. The results make sense intuitively as high wind speed could cause blowing snow effects or impair the visibility of drivers during snow storms. This is similar to results from the literature e.g. Knapp et al (2000). The elasticity value for wind speed shows that a 1% increase in precipitation intensity will cause the mean number of accidents to increase by 0.08%.

- **Monthly ID**

  The general belief is that winter event starts experience more accidents than the end. This effect was tested by including factors for different months to capture the effects of this early season trend. Monthly IDs were included both in categorical and continuous forms. Though both were significant, the categorical monthly factors make more sense than the continuous ones as different months could have different effects. This also improved the model fit. Results from this analysis show that the start of winter is more crash prone compared to other months. This could be due to adaptation of drivers to driving in snow storm conditions with the passage of winter season. Similar results have been reported in the literature e.g. Eisenberg and Warner (2005), Maze and Hans (2007) etc.

- **Hourly ID**

  In addition to the monthly ID for seasonal variation, hourly IDs were included in the analysis to test the effects of first hour (FH) or first two hours (SH) on safety. Effect of first hour was found to be significant with a negative sign. This means that first hour of the storm is safe compared to other hours. This could be due to the good road surface condition at the very start of the event compare to the later hours.

- **Site Specific Variables**

  Site specific variables -which were included in the analysis to capture the possible effect of other route specific factors (such as location, driver population, and road geometry, on road safety)- were also found to be significant. Different types of variables such as regions, road types and individual sites were tested and dummy variables representing individual sites were found to give better results. This has been discussed in section 4.3.3.

4.4 Model Application

The calibrated models could be applied for evaluating the safety benefit of alternative winter road maintenance Level of Service (LOS) goals for a specific maintenance route under a specific snow storm event. The EBD model is more suitable for assessing the performance of different maintenance routes on a seasonal basis whereas the HBD model is best suited for within event assessment of alternative maintenance operations.

4.4.1 Application of EBD Model

To show the application of the developed model (EBD-GNB7), the model is applied to two hypothetical case studies using Patrol route 2 with a length of 28 km (selected for this example). The first case study is to assess the safety implications of adopting different bare pavement (BP) recovery times, one of the critical policy variables in winter road maintenance operations. The snow event is assumed to last eight hours: four hours of precipitation and four hours of BP recovery time. Average values from **Table 4 -3**, EBD data are used for this assumed snow storm.

In the first case, it is assumed that little maintenance work was done and the road surface conditions would deteriorate from bare dry to bare wet passing through snow covered conditions. Two road surface conditions are considered, namely, snow covered and bare pavement. For snow covered conditions, the corresponding RSI is assumed to be 0.2 (average condition within the snow storm) while the bare pavement surface is assumed to have a RSI of 0.8. It is also assumed that before the start of the storm, road surface is dry with a RSI of 1.0. For this scenario, the average RSI is 0.356 ((1.0 + 7.0 x 0.2 + 0.8) / 9). The mean number of accidents in this case is 1.439.

Now, we consider the alternative scenario of reducing the BP recovery time to three hours. This means reducing the storm duration to seven hours (four hours of precipitation and three hours of BP recovery time). Under the same conditions, the new average RSI is 0.375 ((1.0 + 6 x 0.2 + 0.8) / 8). The mean number of accidents in this case is 1.214, that is, a 16 % reduction.

In the second case it is assumed that some other maintenance work such as plowing has been done in the second hour raising RSI to 0.8 then dropping in a linear way to 0.4 at the end of fourth hour due to precipitation and remain so until the 7th hour after which it raises back to RSI = 0.8. For this case the new average RSI is 0.556 ((1.0 + 0.2 + 2*0.8+0.6+4*0.4) / 9). The mean number of accidents in this case is 0.595, that is, a 59 % reduction.

4.4.2 Application of HBD Model

This section illustrates the potential application of HBD-GNB4 model (hourly events) for evaluating the safety benefit of maintenance operations. Two examples are considered, as discussed in the following section.

In the first example, the safety benefit of some WRM operations e.g. ploughing and salting timing have been assessed. Using overall average values from **Table 4-4,** we assume a snow storm with 8 hour duration for patrol 2. Furthermore, the road surface conditions of this route, as represented by RSI, are assumed to vary over the event as follows:

- At the start of the event, the road surface is bare and dry with a RSI of 1.0 at the start of the first hour.
- At the end of the first hour, the road surface becomes “SNOW PACKED WITH ICY” with an RSI value equal to 0.2.
- In the case that no maintenance operations are done, the road surface would remain in this condition (with RSI = 0.2) until the end of the event (i.e., 8 hours).

- For the case with maintenance operations, a combination of ploughing and salting operations is applied, which would improve the road surface condition to a mixed state of slushy, wet, and partially snow covered with an equivalent RSI of 0.8.
- It is assumed that the effect of salt would last for five hours. The RSI of the road surface conditions would decrease linearly from 0.8 to 0.2 (SNOW PACKED WITH ICY) within the storm period.

The safety benefit of winter road maintenance is defined as the difference in the expected total number of accidents between the conditions of with and without winter road maintenance over the storm period. To show how this benefit is calculated, we consider the above storm with the maintenance operations (ploughing and salting) completed at the start of the second hour. As shown in **Figure 4-9**, the shaded area represents the difference between doing nothing (no maintenance) and maintenance (salting & ploughing).

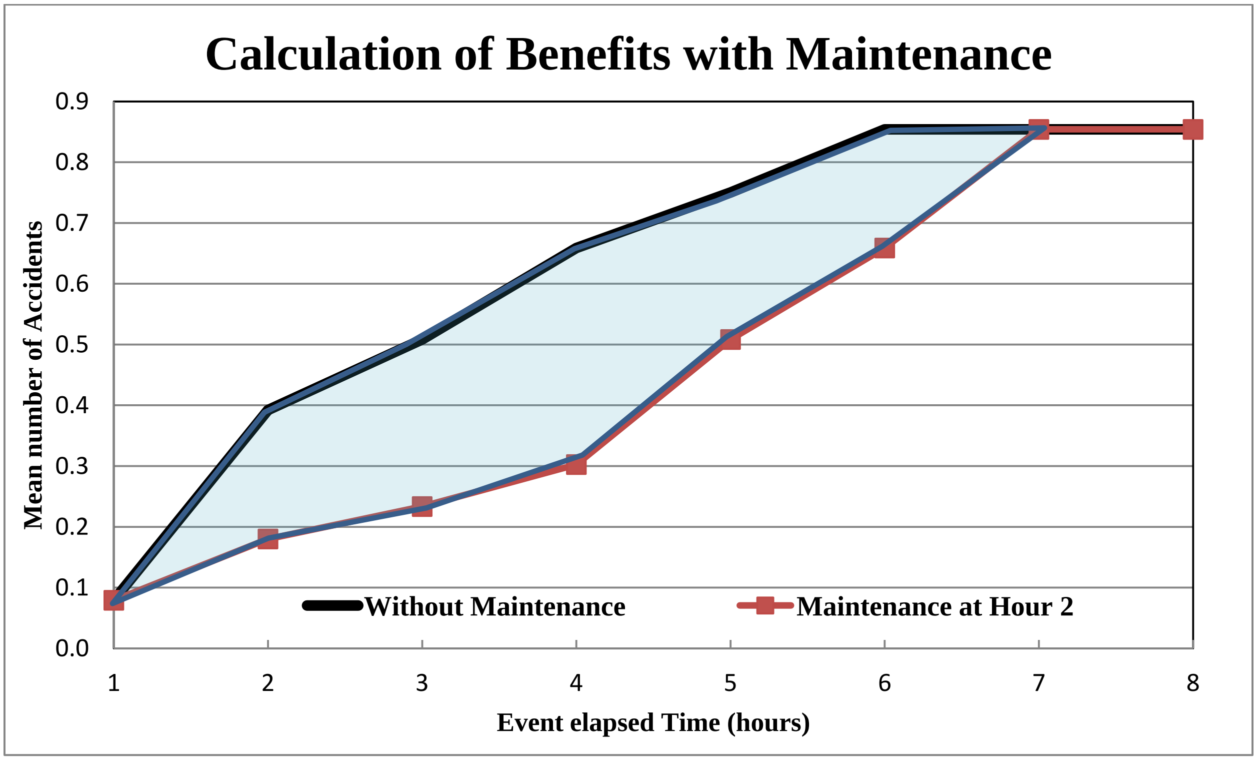

Figure 4-9: Calculation of safety benefit of maintenance operation

Similarly, the safety benefit of other maintenance start/completion times can be calculated, as shown in **Figure 4-10** (2nd, 4th and 6th hour).

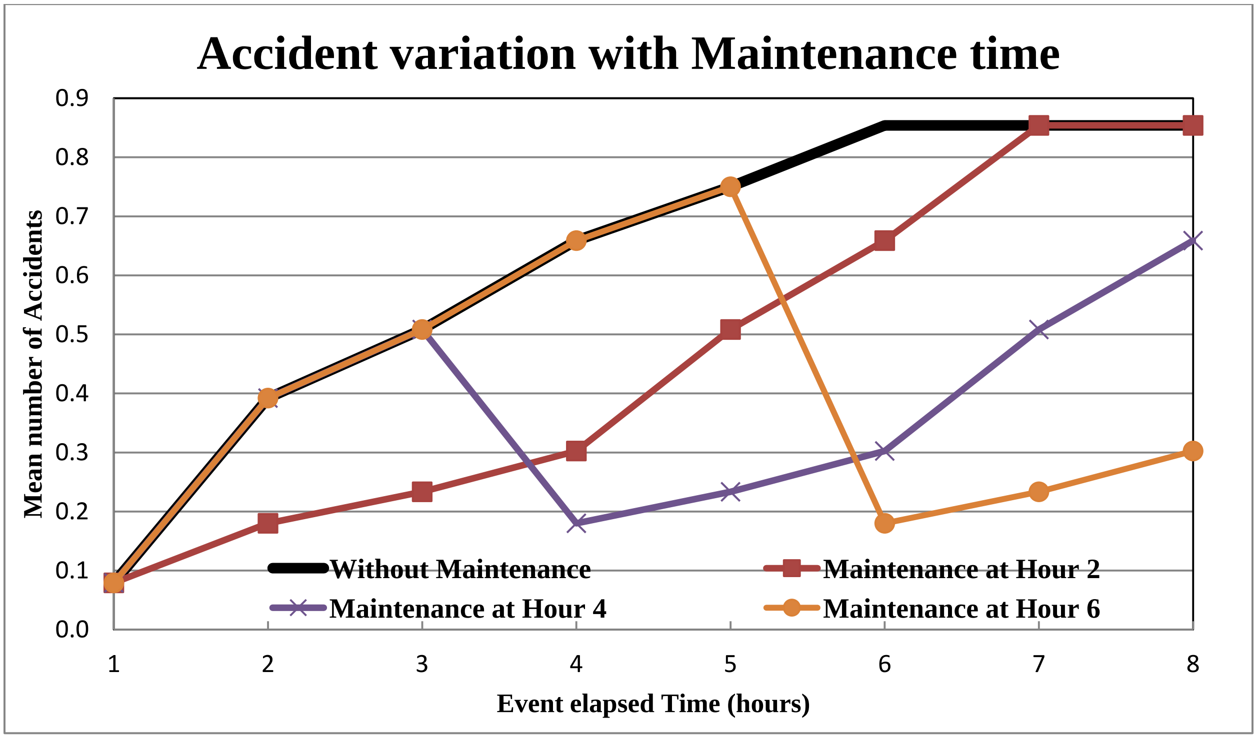

Figure 4-10: Safety benefit vs. maintenance timing

In the second example, the HBD model is applied to assess the safety implications of bare pavement (BP) regain policy. Continuing the above example it is assumed that the storm lasted for 8 hours and BP was recovered eight hours after the precipitation stopped, which met the BP standard for Class 1 highways (MTO, 2003).

Figure 4-11 shows the potential benefit of shortening the BP regain time, as represented by the relative decrease in the expected number of accidents. As shown in **Figure 4-11**, the relative benefit is proportional to the BP regain time. For example, the expected safety benefit of reducing the BP regain time from eight hours to four hours would be a reduction of accidents by over 50% for this highway section over the eight hours. These values can be converted into monetary values by multiplying them by average accident cost.

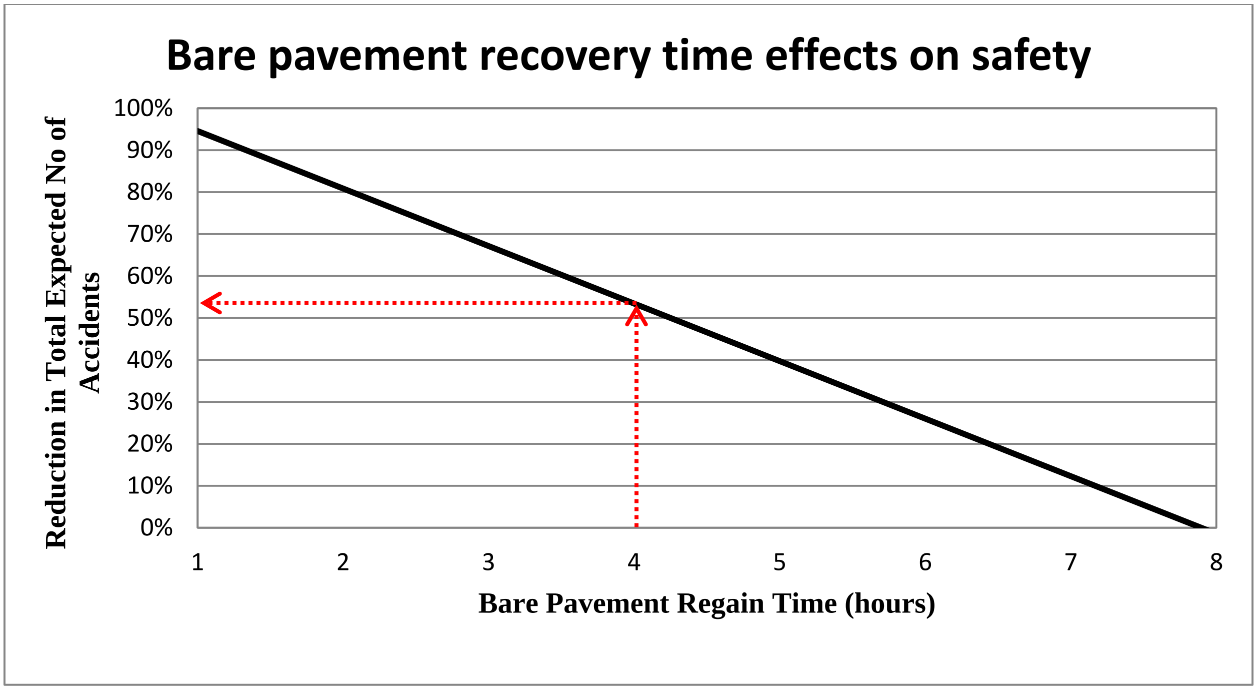

Figure 4-11: Effect of bare pavement regain time on safety

4.5 Summary

Accident frequency models were developed using winter storm data compiled for six winter seasons (2000 to 2006) with the objective to link WRM operations with safety. RSI was used as a surrogate measure for the effects of WRM. Other factors related to weather, traffic and road features (through site ID) were also accounted for in the analysis. A total of 31 highway routes across Ontario were used as the study sites in the analysis. Two different datasets were formed, namely, event-based data (EBD) and hourly based data (HBD). The EBD aggregates data by snow storm events. The HBD includes hourly records of longitudinal nature with a two level data structure: with hours in each snow storm nested within an event. Two issues were identified that could distort the parameter estimates of the models 1) Aggregation problem and 2) Correlation problem. To account for these issues different modeling approaches were used. It was however found that correlation for accidents within storms is weak. This was further confirmed by the fact that GNB has a better fit to the data than the two level PLN model. Aggregation on the other hand was found to affect the parameter estimate of the models.

NB and GNB models were calibrated for EBD, whereas multilevel PLN and GNB models were calibrated for HBD. Models were developed for each individual site and for datasets pooled together. GNB was found to best fit the data for most of the individual sites and the combined sites. The combined datasets (HBD and EBD) were formed to check the effects of different site specific features. It was found that the addition of site specific features improve the model fit. RSI was to be found significant for all the models and datasets. Weather factors such as visibility, wind speed, precipitation, and air temperature were also found to have statistically significant effects on road safety. All the models were consistent in terms of effects of different variables (as shown by their sign of coefficients).

The EBD models are useful to quantify the effects of different maintenance service standards and policies with limited information on weather events and traffic. This knowledge could be sufficient for determining the cost-effectiveness of alternative winter maintenance polices and operations. On the other hand, HBD models have a higher level of fidelity capable of providing more accurate estimates on road accidents. As a result, they are useful for determining the effects of different treatment operations. This was demonstrated through examples. This methodology can be applied to any other roadway sections with detailed data on road weather conditions, traffic, maintenance, and accidents.

Chapter 5

COLLISION SEVERITY ANALYSIS

As described in Chapter 1, the main objective of this research is to develop a methodology to evaluate the performance of alternative WRM operations using safety as a performance function. Chapter 4 has focused on developing collision frequency prediction models and identifying contributing factors linked to collision frequency during snow storms. This chapter describes efforts to develop consequence models for predicting the severity level of a given snow storm collision and identifying factors that affect these collisions. The consequence models can be used to improve the collision cost estimates that are required by the cost-benefit analysis framework for evaluating alternative WRM decisions. This is done by accounting for the different severity classes with different financial implications.

5.1 Modeling Approach

As discussed in the literature review section (Chapter 2), most of the past research efforts on severity modelling have been dedicated to quantifying the effects of different road, driver and vehicle characteristics on the severity levels of various collisions. Furthermore, few studies have dealt specifically with analysing the severity of collisions under winter weather conditions. Three different approaches can be used for collision severity analysis: a) incorporating severity into the collision frequency models by modeling collisions classified by severity types (Bijleveld 2005; Ma and Kockelman 2006; Park and Lord, 2007; Ma et al 2008); b) modeling the conditional probability of experiencing each severity level for a given collision (Shankar and Mannering 1996; Dissanayake and Lu 2002; Yao 2004; Saccomanno et al 1996; Wong et al 2008); and c) establishing aggregate models for the ratios of individual severity levels based on data averaged over given spatial and temporal units (Edwards 1998). In this research, we adopted the second approach for three reasons 1) different factors could have different effects on collision occurrence and severity (e.g., seat belt use has nothing to do with collision occurrence, but is an important factor in severity analysis.); 2) data that could be used for joint models is limited in nature because most of the data is collected after the collision has happened (Savolainen et al 2011) and 3) consequence outcomes and injury data are at the individual, vehicle or accident level.

As discussed in Chapter 2, there are several alternative models that could be used for representing collision severity outcomes using disaggregate collision data. Most of the models are extensions of the multinomial Logit models based on the assumption of independent severity classes (e.g. Nassar et al, 1994; Saccomanno et al 1996; Shankar et al 1996; Carson and Mannering 2001; Dissanayake and Lu 2002; Jones and Jørgensen 2003; Donnell and Mason 2004; Shankar et al 2005; Lenguerrand et al. 2006; Milton et al 2008; Lee and Abdel-Aty 2008).

In this analysis we apply three different logistic models – binary logit, multinomial logit and ordered logit regression techniques. These models are mostly used in previous research for collision severity analysis. These models can be applied in a standard or multilevel framework to account for the hierarchical structure of the collision data as described in Section 2.4.4. The conventional approach to collision severity analysis is aggregating the data at the collision level (into the level of collisions) and performing the analysis on the resulting collision based data set. This approach ignores the hierarchical nature between involved individuals, vehicles and collisions. Without accounting for this inherent hierarchical structure, the resulting models might suffer from both issues of aggregation and correlation existing between the people in the same vehicle and also vehicles in the same collision.

The first modeling structure considered is multilevel multinomial logit model (MML). Extending the model structure to account for the three levels of aggregation, **Equation 2 – 18** can be written as:

$$\ln\left[\frac{p(y=1/X)}{p(y=0/X)}\right] = \beta_{10} + \sum_{n=1}^{N} \beta_{1n} X_{1ijkn} + U_{jk} + V_k$$

$$\ln\left[\frac{p(y=2/X)}{p(y=0/X)}\right] = \beta_{20} + \sum_{n=1}^{N} \beta_{2n} X_{2ijkn} + U_{jk} + V_k \qquad \textbf{(5 – 1)}$$

where i, j and k represents occupant, vehicle and collision levels respectively; U_{jk} and V_k denote second level (vehicle) and third level (collision) random effect factors which are assumed to follow a logistic distribution; β is a model coefficient to be estimated and X_{ijk} represents a set of explanatory variables at the individual level (again the subscript "i" denotes occupant). U_{jk} remains constant for occupants within a vehicle but varies across vehicles and collisions. Similarly V_k is constant for vehicles in a collision but varies across collisions. U_{jk} and V_k are obtained by considering the intercept as a random parameter, as discussed in Section 2.4.4.

The second modeling structure is multilevel sequential binary logistic model (MBL), which is extended from **Equation 2 – 17** to account for the three levels of aggregation, as shown in Equation 5-2. This model is calibrated at each split of **Figure 5 – 2**.

$$\ln\left[\frac{p(y=1)}{p(y=0)}\right] = \beta_0 + \sum_{n=1}^{N} \beta_n X_{ijkn} + U_{jk} + V_k \tag{5 – 2}$$

The third modeling structure considered in this research is multilevel ordered logit model (MOL). The mathematical form of a multilevel ordered Logit model for a three level data structure is shown in **Equation 5 – 3**.

$$Log\left[\frac{Severity_{ijk}^{s}}{Severity_{ijk}^{r}}\right] = \beta_0 + \beta_1 X_{ijk} + U_{jk} + V_k \tag{5 – 3}$$

An important aspect of ordered logit models is the proportional odds (or parallel slopes) assumption, where the variables are assumed to have the same slope across all levels of severity/outcome (Kosmelj and Vadnal 2003; Dissanayake, Sunanda 2004; Kamarudin et al. 2007) with the exception of the intercept (Jung et al. 2010). Results of ordered logit models are therefore unidirectional (show either an increase or decrease in severity) and are thus very easy to interpret. This unidirectional effect can sometimes lead to undesirable effects where a variable could cause the probability of high or low severity collision to increase at the cost of the other (Savolainen and Mannering 2007)

5.2 Data Sources

Collision data is collected and maintained in Ontario as person based data where detailed information about each person and vehicle is recorded. For the purpose of this research, a data set containing all collisions occurred over six winter seasons (2000-2006 with each winter season covering seven months from October to April) is prepared. This data set is called All Weather Collision Data (AWCD), and contains 13,775 collisions involving 19,635 vehicles and 39,564 individuals. Collisions are categorized into five distinct injury severity levels as follows:

1. **No Injury (NI):** where the person sustained no injury,

2. **Minimal Injury:** where the involved person has minor abrasions or pain complaints but did not go to the hospital,
3. **Minor Injury:** where the involved person was treated in the emergency room but not admitted.
4. **Major Injury:** where the involved person was admitted to the hospital either for treatment or observation.
5. **Fatality:** where the involved people died within 30 days of the collision or at the site of a collision.

Minimal Injury and No Injury collisions were grouped together into one category because they are similar in terms of consequence. Similarly, major injuries and fatalities were also grouped into a single category. This merging of categories will also take care of the possible correlation that could exist between such closely related outcomes of a collision severity (Hutchings et al. 2003; Savolainen et al. 2011). The hierarchic structure of collision data is shown in **Figure 5 – 1** which shows that for a given collision, vehicles are nested within the collision and persons are nested within vehicles and each person could have a given level of severity.

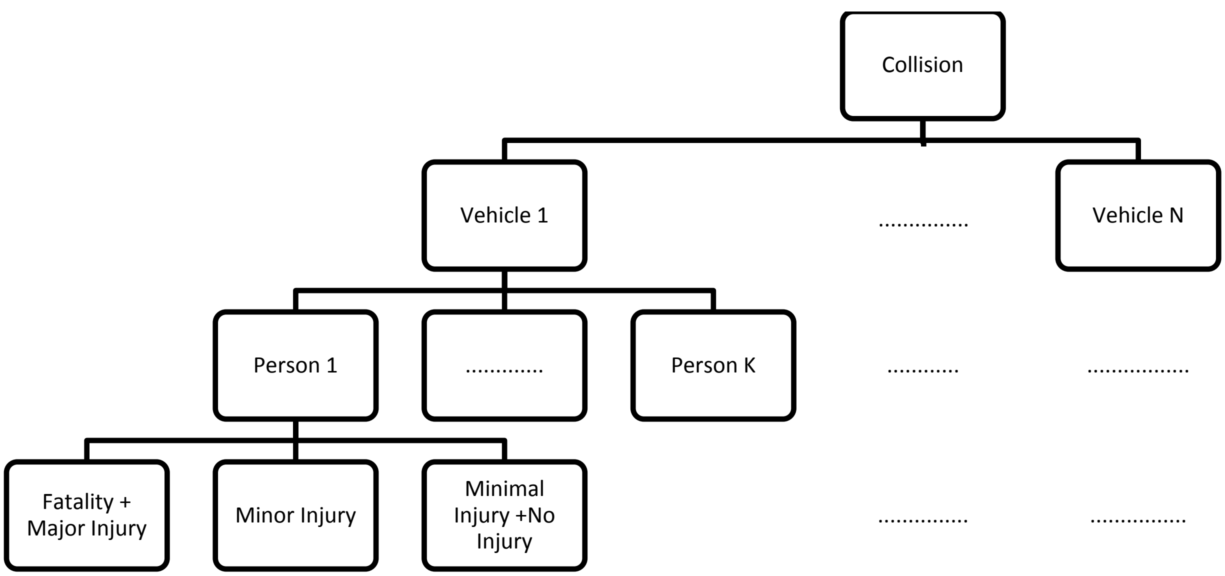

Figure 5-1: Hierarchical structure of collision data

Data from other sources such as weather and traffic were merged with the person based collision data based on date, time and location for the 31 patrol routes identified in Chapter 3. This data was then aggregated at the vehicle level and then at the collision level (**Figure 3 – 8**) resulting in three levels of data aggregation (three datasets): collision based records - one level including details on collisions but aggregated information about vehicles and occupants, vehicle based records - two levels including details on both collision and vehicle details but aggregated information about occupants, and occupant based records - three levels including details on collisions, vehicles and occupants. These three data sets were used to develop severity models of different aggregation levels for examining the effect of data aggregation on model performance. The disaggregate approach makes full use of the information available in the collision data while at the same time accounting for possible correlation in severity levels of individuals or vehicles involved in a given collision. For the vehicle and collision based data, severity levels were assigned to the respective vehicles and collisions as per the classification scheme presented in **Figure 5 - 2**. This classification scheme was not used for occupant based data, as each person has a unique injury severity level.

In the next step, collisions that occurred during snow events are extracted from AWCD to form the snow storm event collision data (SECD). This data set contains 3,035 collisions involving 4,069 vehicles and 8,081 individuals.

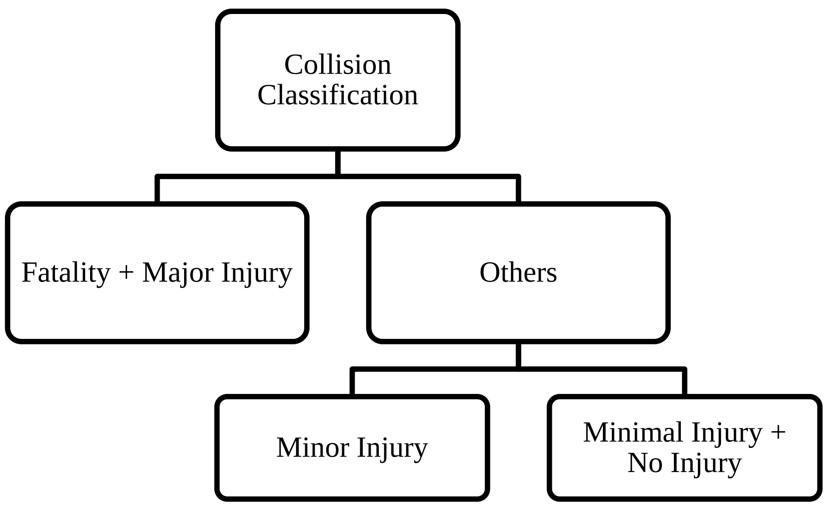

Figure 5-2: Collision data classification scheme (vehicle and collision based data)

5.3 Exploratory Data Analysis

A large number of factors can influence the severity of collisions under winter conditions (Miaou et al. 2003; Andrew et al. 1998). These factors can be grouped into four categories, namely; road driving conditions, as well as vehicle, traffic and driver conditions. Road driving conditions include road geometry, environment, and pavement surface conditions etc. The latter are affected by weather and maintenance operations and are of particular interest for the cost benefit analysis of alternative WRM operations. Details of the variables used in this analysis are given in **Table 5 – 1**. As shown in this table, different sets of variables are considered in analyzing the three datasets.

Table 5-1: List of Variables Used in the Analysis

Category	Variable	Definition
Road characteristics	Road classification	Freeway = 1, Kings Highway multilane = 2, Kings Highway two lane*** = 3
	Road alignment	Straight on Level*** = 1, Straight on Hill = 2, Curve on Level = 3,Curve on Hill = 4
	Number of lanes	Number of lanes
	Collision location	Intersections = 1, Segment*** = 2, Bridges/ Underpasses= 3
	Speed limit	Km/hr
Weather and environment conditions	Light	Light + Dawn = 1, Dark + Dusk*** = 2
	Precipitation type	Other*** = 0, Freezing rain/ snow = 1
	Hourly precipitation	Precipitation intensity in “cm”
	Temperature	Measured in ^{o}C
	Wind speed	Km/hr
	Visibility	Km
	Road surface condition	Road Surface Condition in winter i.e. icy, snow covered etc. represented by RSI
	Day	Weekdays = 0, Weekends*** = 1
Vehicle	Vehicle type **	SUVs/Car/Station Wagon*** = 1, Van = 2, Large Trucks etc. = 3
	Vehicle condition**	Otherwise = 0, Defective*** = 1
	Vehicle age **	In years
Driver/Person	Driver age **	In years
	Driver sex **	Male = 1, Female*** = 2
	Driver condition at time of collision**	Otherwise*** = 0, Normal = 1
	Position in vehicle *	Front = 1, Rear*** = 2
	Safety equipment used*	Used Safety Device = 0, Not Used or Bad Use*** = 1
Traffic	Hourly traffic volume	Ln(hourly traffic volume)

*Used for occupant based data only; ** Used for vehicle and occupant based data only; ***Base category

Appendix – O (Table O – 1 to O – 9) illustrates the distribution of injury severity according to different variables. **Figure 5 – 3** to **5 – 6** demonstrates the distribution of injury severity for some of the variables such as RSI, traffic, visibility and wind speed from the AWCD occupant level data. It can be observed from these figures that any improvement in RSI, increase in traffic volume and visibility reduces the severity of a collision across all levels. Moreover the relation between severity of a collision and traffic suggests a non linear relationship. In this analysis we use Ln(traffic) to depict this relationship. Wind speed decreases collision severity from minor injuries to minimal injuries and No Injury, but shows no effects on fatalities and major injury severity collisions.

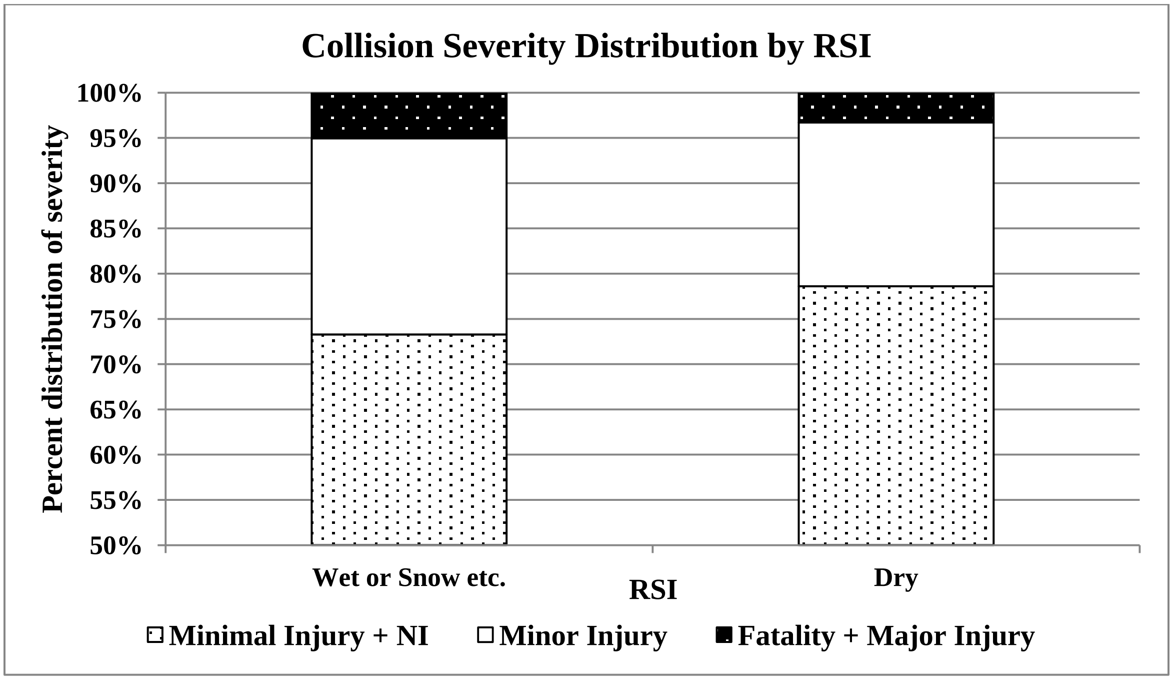

Figure 5-3: Collision severity distribution by RSI- AWCD

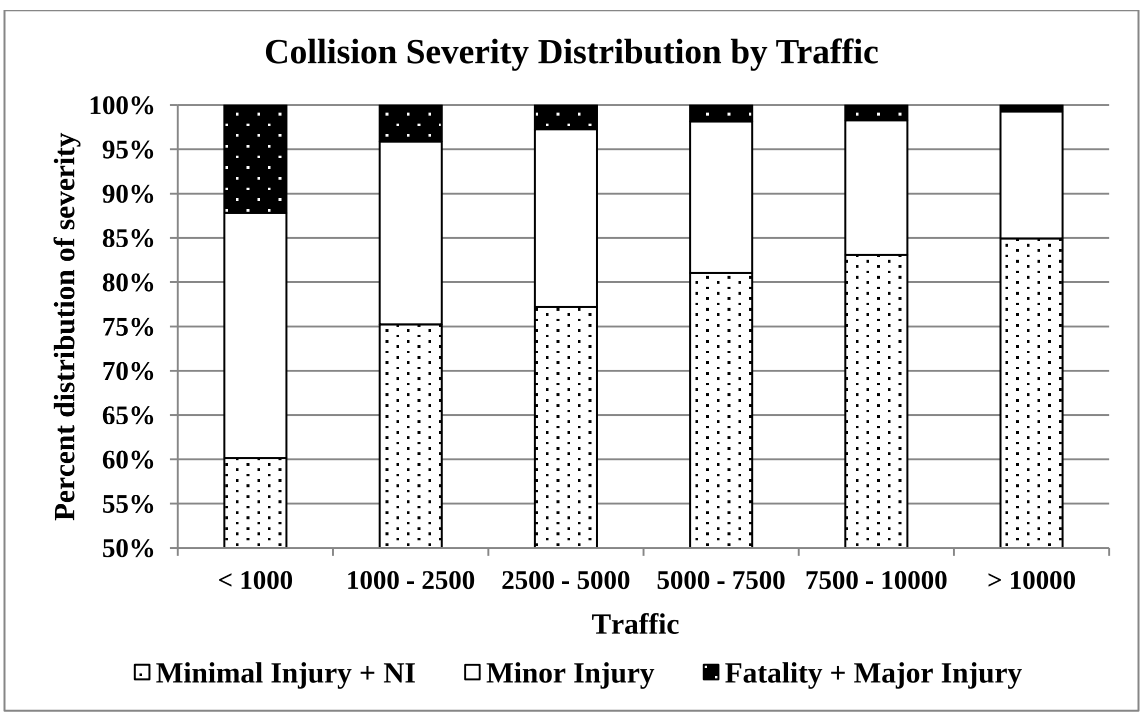

Figure 5-4: Collision severity distribution by traffic- AWCD

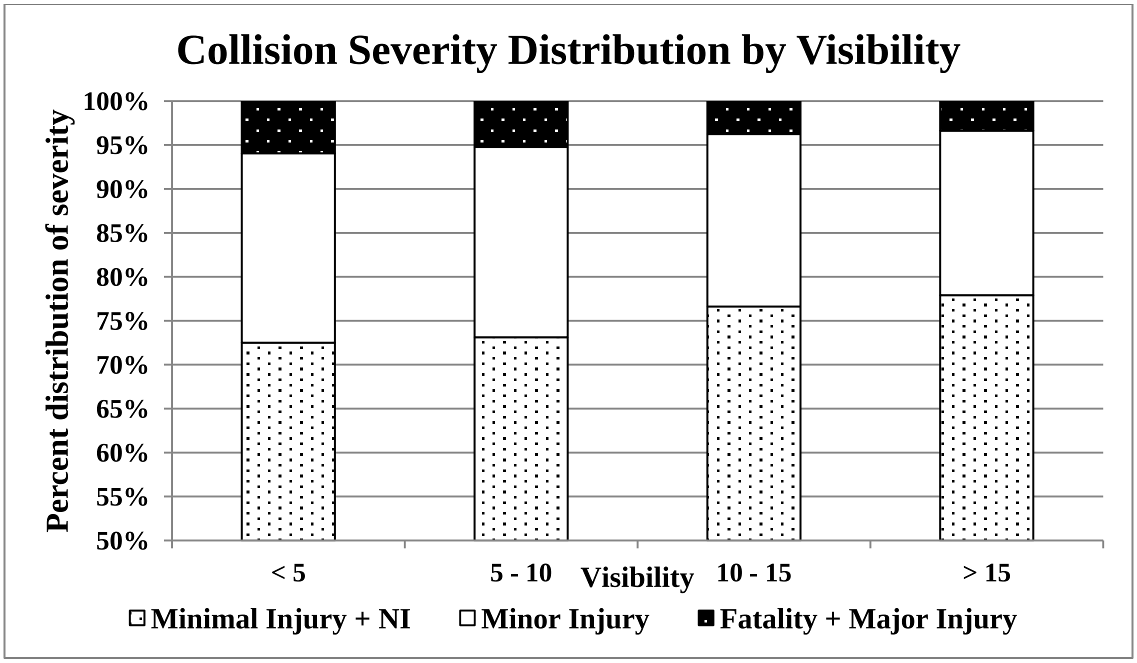

Figure 5-5: Collision severity distribution by Visibility - AWCD

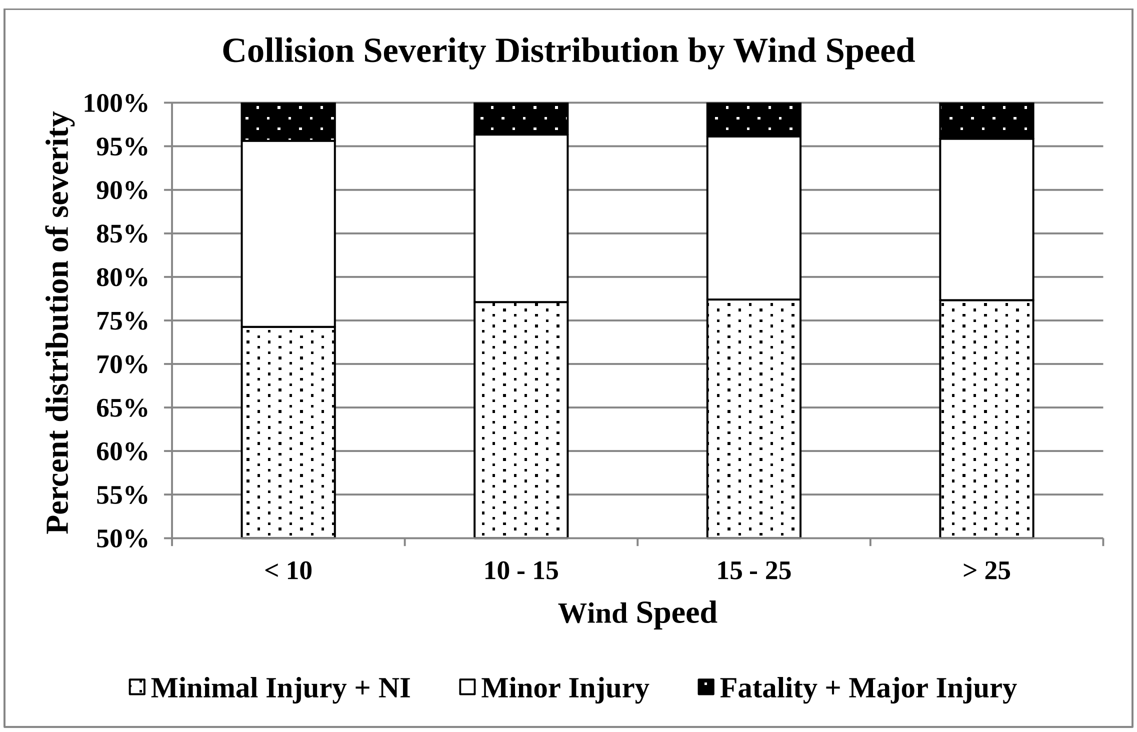

Figure 5-6: Collision severity distribution by wind speed - AWCD

Table 5 - 2 and **5 – 3** shows the changes in the proportions of different types of injury severity levels due to aggregation at each step for the AWCD and SECD, respectively.

As shown in **Figure 5 – 1**, a collision may involve several vehicles, and the occupants of the involved vehicles may experience different levels of injury severity. As a result, modeling the collision severity at the collision level will likely result in the loss of information and a misrepresentation of certain severity levels, as shown in **Table 5 - 2** and **5 – 3**. For example, if we aggregate data for a collision with three fatalities and two involved vehicles, the fatality count for occupant, vehicle and collision based data sets will be 3, 2 and 1, respectively.

Table 5-2: Percent Change in Collision Severity Distribution due to Data aggregation – AWCD

All Sites	Minimal Injury + No Injury	Minor Injury	Fatality + Major Injury
Occupant based data	76.45%	19.55%	4.01%
Vehicle based data	64.67%	30.07%	5.26%
Collision based data	53.35%	40.15%	6.50%

Table 5-3: Percent Change in Collision Severity Distribution due to Data aggregation – SECD

All Sites	Minimal Injury + No Injury	Minor Injury	Fatality + Major Injury
Occupant based data	73.27%	21.64%	5.09%
Vehicle based data	61.15%	32.69%	6.17%
Collision based data	51.86%	41.32%	6.82%

As discussed previously, most past efforts on severity modeling consider all collisions that occurred over an analysis period, regardless of weather conditions. One of the problems with this approach is that a disproportional number of collisions are associated with normal weather and road surface conditions. As a result, the effects of winter related factors might be under-represented relative to normal weather conditions. The latter is not applicable for evaluating the effects of alternative winter road maintenance policies and methods. In this research, we focus on developing severity models for snow storm collisions; but for the purpose of comparison, we will also develop models for all weather collisions (Section 5.4). The alternative models proposed in Section 5.1 are calibrated for both all-weather collisions and snow storm collisions. Differences in modeling results are compared between these two data sets.

5.4 Modeling of All Weather Collisions

MLwin[6] was used to calibrate the three alternative models discussed in the previous section using the all-weather collision data set (AWCD). **Table 5 - 4** to **5 - 6** provides the calibration results. A positive sign is used as an indicator of increase in severity level with respect to the associated variable. For evaluating the effect of individual factors, their elasticities are calculated and given in **Table 5 – 7**. For a continuous variable X_{ki}, elasticity was for a particular collision severity outcome "i" is computed as:

$$E_{X_{ki}}^{P(i)} = [1 - P(i)]\beta_{ki}X_{ki} \qquad \textbf{(5 – 4)}$$

where P(i) is the probability of collision severity outcome "i" and β_{ki} is the coefficient associated with variable X_{ki}. For categorical variables elasticity is calculated as E = [exp (β) – 1]/ exp (β) (Lee and Mannering 2002; Ulfarsson et al 2006; Malyshkina and Mannering 2008). In Table 5 – 8 prediction results from the models for the AWCD are compared with the observed ratios. A detailed discussion on model comparisons and factors affecting collision severity is provided in the following section.

[6]Rasbash, J., Charlton, C., Browne, W.J., Healy, M. and Cameron, B. (2005) ***MLwin Version 2.22***. Centre for Multilevel Modeling, University of Bristol.

Table 5-4: Results for Collision Based Model – AWCD

Categories	Variable	MBL* Fatal		MBL Minor		MOL*		MML*** - Fatality VS NI		MML-Minor VS NI	
		Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
	Constant	-0.856	0.021	0.020	0.917			0.034	0.926	0.016	0.931
Road Type	Freeways	-0.114	0.476	0.017	0.875	-0.159	0.101	-0.101	0.523	0.027	0.789
	Multilane Kings	0.287	0.089	-0.038	0.772	-0.044	0.704	0.262	0.123	-0.032	0.791
	2 Lane Kings	0.000		0.000		0.000		0.000		0.000	
Other	Light/Dawn	-0.207	0.004					-0.181	0.009		
	Dark/Dusk	0.000						0.000			
	Week Days	-0.197	0.009	-0.097	0.018	-0.137	0.000	-0.247	0.001	-0.096	0.014
	Week Ends	0.000		0.000		0.000		0.000		0.000	
Road Related	Road Alignment - Straight on Hill			0.186	0.004	0.180	0.003			0.172	0.004
	Road Alignment - Curve on level			-0.004	0.955	0.014	0.832			-0.008	0.902
	Road Alignment - Curve on Hill			-0.021	0.795	-0.038	0.617			-0.014	0.852
	Road Alignment - Straight on level			0.000		0.000				0.000	
	Speed Limit	0.013	0.001	0.008	0.000	0.010	0.000	0.014	0.000	0.008	0.000
	Number of lanes	-0.103	0.000	-0.083	0.000	-0.087	0.000	-0.127	0.000	-0.082	0.000
	RSI	0.317	0.018					0.309	0.018		
Weather	Weather - Freezing Rain, Snow					-0.085	0.048				
	Weather - Other					0.000					
	Wind Speed (Km/hr)			-0.005	0.012	-0.005	0.012			-0.005	0.012
Traffic	Ln(Traffic)	-0.320	0.000	-0.056	0.005	-0.135	0.000	-0.339	0.000	-0.054	0.004
	μ_1					-0.881	0.000				
	μ_2					1.742	0.000				
	-2*log likelihood (null):-	508.443		18437.2		19301.4		19301.4			
	-2*log likelihood (full):-	-3340.050		17892.1		15804		14944			
	Collision level observations	13775		12880		13775		13775			

* Multilevel Binary Logit Models; ** Multilevel Ordered Logit Models; *** Multilevel Multinomial Logit Models

Table 5-5: Results for Vehicle Based Model – AWCD

Categories	Variable	MBL Fatal		MBL Minor		MOL		MML - Fatality VS NI		MML-Minor VS NI	
		Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
	Constant	-0.488	0.260	0.397	0.042			0.487	0.248	0.397	0.037
Road Type	Freeways	0.029	0.868	0.165	0.102	0.026	0.780	0.111	0.519	0.179	0.062
	Multilane Kings	0.297	0.112	0.030	0.804	0.011	0.920	0.318	0.087	0.037	0.746
	2 Lane Kings	0.000		0.000		0.000		0.000		0.000	
Other	Light/Dawn	-0.175	0.021					-0.184	0.012		
	Dark/Dusk	0.000						0.000			
	Week Days	-0.159	0.047					-0.163	0.034		
	Week Ends	0.000						0.000			
	Collision Location - Intersections	-0.148	0.294			-0.134	0.031	-0.227	0.100		
	Collision Location - Bridges/ Underpasses	0.665	0.021			0.240	0.124	0.707	0.009		
	Collision Location - Segment	0.000				0.000		0.000			
Road Related	Road Alignment - Straight on Hill			0.202	0.000	0.193	0.001			0.198	0.000
	Road Alignment - Curve on level			0.146	0.032	0.159	0.013			0.137	0.032
	Road Alignment - Curve on Hill			0.125	0.105	0.098	0.185			0.129	0.077
	Road Alignment - Straight on level			0.000		0.000				0.000	
	Speed Limit	0.014	0.000	0.008	0.000	0.008	0.000	0.015	0.000	0.008	0.000
	Number of lanes	-0.109	0.000	-0.080	0.000	-0.085	0.000	-0.132	0.000	-0.080	0.000
	RSI			-0.322	0.000	-0.266	0.000			-0.312	0.000
Driver	Driver Age (years)	0.007	0.020	0.002	0.046	0.003	0.003	0.008	0.008	0.003	0.003
	Driver - Male	0.139	0.078	-0.241	0.000	-0.175	0.000			-0.242	0.000
	Driver - Female	0.000		0.000		0.000				0.000	
	Driver Condition - Normal	-0.605	0.000	-0.170	0.000	-0.285	0.000	-0.711	0.000	-0.177	0.000
	Driver Condition - Other (drinking etc)	0.000		0.000		0.000		0.000		0.000	

Table 5 – 5: Cont.

Categories	Variable	MBL Fatal		MBL Minor		MOL		MML - Fatality VS NI		MML-Minor VS NI	
		Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Vehicle	Vehicle Age (years)			0.013	0.001	0.012	0.000			0.013	0.000
	Vehicle Type - Vans	0.192	0.021	0.116	0.003	0.129	0.000	0.217	0.007	0.112	0.003
	Vehicle Type - Large Trucks etc	0.042	0.771	-0.612	0.000	-0.495	0.000	-0.089	0.519	-0.595	0.000
	Vehicle Type - Car/Station Wagon	0.000		0.000		0.000		0.000		0.000	
Weather	Wind Speed (Km/hr)			-0.006	0.003	-0.006	0.003			-0.006	0.003
Traffic	Ln(Traffic)	-0.384	0.000	-0.139	0.000	-0.201	0.000	-0.447	0.000	-0.141	0.000
	μ_1					-1.195	0.000				
	μ_2					1.230	0.000				
	-2*log likelihood (null):-	-3834.8		24302.0		20777.2		20777.2			
	-2*log likelihood (full):-	-11816.4		22859.8		13911.2		11398.3			
	Variance at collision level	2.352	0.000	0.199	0.000	0.272	0	0.205		0.000	
	Variance at vehicle level	3.29	0	3.29	0	3.29	0	3.29		0	
	Collision level observations	13775		13060		13775		13775			
	Vehicle level observations	19635		18603		19635		19635			

Table 5-6: Results for Occupant Based Model – AWCD

Categories	Variable	MBL Fatal		MBL Minor		MOL		MML - Fatality VS NI		MML-Minor VS NI	
		Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
	Constant	0.341	0.504	0.559	0.003			1.349	0.009	0.561	0.002
Road Type	Freeways	0.054	0.791	0.105	0.259	0.012	0.892	0.048	0.812	0.130	0.149
	Multilane Kings	0.340	0.134	0.103	0.353	0.085	0.409	0.297	0.187	0.094	0.380
	2 Lane Kings	0.000		0.000		0.000		0.000		0.000	
Other	Light/Dawn	-0.159	0.058			-0.057	0.075	-0.166	0.043		
	Dark/Dusk	0.000				0.000		0.000			
	Collision Location - Intersections	-0.151	0.336			-0.133	0.024	-0.189	0.223		
	Collision Location - Bridges/ Underpasses	0.823	0.015			0.247	0.100	0.873	0.007		
	Collision Location - Segment	0.000				0.000		0.000			
Road Related	Road Alignment - Straight on Hill			0.131	0.017	0.131	0.013			0.133	0.012
	Road Alignment - Curve on level			0.180	0.004	0.193	0.002			0.165	0.007
	Road Alignment - Curve on Hill			0.198	0.007	0.168	0.018			0.190	0.007
	Road Alignment - Straight on level			0.000		0.000				0.000	
	Speed Limit	0.016	0.001	0.009	0.000	0.008	0.000	0.018	0.000	0.009	0.000
	Number of lanes	-0.122	0.000	-0.079	0.000	-0.084	0.000	-0.141	0.000	-0.078	0.000
	RSI			-0.295	0.000	-0.248	0.000			-0.306	0.000
Driver	Driver Age (years)	0.007	0.000	0.004	0.000	0.004	0.000	0.008	0.000	0.004	0.000
	Driver - Male			-0.377	0.000	-0.329	0.000			-0.381	0.000
	Driver - Female			0.000		0.000				0.000	
	Driver Condition - Normal	-0.561	0.000			-0.147	0.000	-0.590	0.000		
	Driver Condition - Other (drinking etc)	0.000				0.000		0.000		0.000	

Table 5 – 6: Cont.

Categories	Variable	MBL Fatal		MBL Minor		MOL		MML - Fatality VS NI		MML-Minor VS NI	
		Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Vehicle	Vehicle Age (years)			0.018	0.000	0.016	0.000			0.017	0.000
	Vehicle Type - Vans			-0.287	0.000	-0.263	0.000	-0.190	0.037	-0.288	0.000
	Vehicle Type - Large Trucks etc			-0.910	0.000	-0.790	0.000	-0.442	0.001	-0.886	0.000
	Vehicle Type - Car/Station Wagon			0.000		0.000		0.000		0.000	
	Vehicle Condition - Non Defective	-0.411	0.031			-0.156	0.063	-0.419	0.024		
	Vehicle Condition - Defective	0.000				0.000		0.000			
Person	Position in Vehicle - Front			0.241	0.000	0.215	0.000	0.166	0.062	0.244	0.000
	Position in Vehicle - Rear			0.000		0.000		0.000		0.000	
	Safety equipment - Used	-0.826	0.000	-0.733	0.000	-0.836	0.000	-1.070	0.000	-0.660	0.000
	Safety equipment - Not or bad used	0.000		0.000		0.000		0.000		0.000	
Weather	Wind Speed (Km/hr)			-0.006	0.003	-0.005	0.012			-0.006	0.003
	Visibility (Km)			-0.004	0.046	-0.006	0.003			-0.004	0.046
	Hourly Precipitation (cm/hr)					-0.169	0.039				
Traffic	Ln(Traffic)	-0.418	0.000	-0.166	0.000	-0.208	0.000	-0.474	0.000	-0.169	0.000
	μ_1					-1.566	0.000				
	μ_2					0.702	0.001				
	-2*log likelihood (null):-	-24094.8		37806.7		13896.6		13896.6			
	-2*log likelihood (full):-	-44556.4		33338.5		-4166.57		-11450.9			
	Variance at collision level	8.179	0.000	0.782	0.000	0.936	0	0.785		0	
	Variance at vehicle level	0	0	0.1	0	0	0	0.085		0	
	Variance at occupant level	3.29	0	3.29	0	3.29	0	3.29		0	
	Collision level observations	13775		13375		13775		13775			
	Vehicle level observations	19635		19046		19635		19635			
	Occupant level observations	39564		37979		39564		39564			

Table 5-7: Elasticities for the Three Datasets – AWCD

Variable	MBL Fatal	MBL Minor	MOL	MML-Fatality Vs NI	MML-Minor Vs NI
Occupant Based Model					
Freeways	0.053	0.100	0.012	0.047	0.122
Multilane Kings	0.288	0.098	0.089	0.257	0.090
Light/Dawn	-0.172		-0.055	-0.181	
Accident Location - Intersections	-0.163		-0.125	-0.208	
Accident Location - Bridges/ Underpasses	0.561		0.280	0.582	
Road Alignment - Straight on Hill		0.123	0.140		0.125
Road Alignment - Curve on level		0.165	0.213		0.152
Road Alignment - Curve on Hill		0.180	0.183		0.173
Driver Age (years)	0.261	0.122	0.122	0.297	0.121
Driver - Male		-0.458	-0.280		-0.464
Driver Condition - Normal	-0.752		-0.137	-0.804	
Vehicle Age (years)		0.072	0.064		0.068
Vehicle Type - Vans		-0.332	-0.231	-0.209	-0.334
Vehicle Type - Large Trucks etc		-1.484	-0.546	-0.556	-1.425
Vehicle Condition - Non Defective	-0.508		-0.144	-0.520	
Position in Vehicle - Front		0.214	0.240	0.153	0.217
Safety equipment - Used	-1.284	-1.081	-0.567	-1.915	-0.935
Speed Limit	1.492	0.685	0.608	1.668	0.680
Number of lanes	-0.838	-0.443	-0.470	-0.963	-0.434
RSI		-0.193	-0.162		-0.198
Wind Speed (Km/hr)		-0.079	-0.066		-0.079
Visibility (Km)		-0.052	-0.078		-0.052
Hourly Precipitation (cm/hr)			-0.010		
Ln(Traffic)	-3.282	-1.064	-1.331	-3.699	-1.075
Vehicle Based Model					
Freeways	0.029	0.152	0.026	0.105	0.164
Multilane Kings	0.257	0.030	0.011	0.272	0.036
Light/Dawn	-0.191			-0.202	
Week Days	-0.172			-0.177	
Accident Location - Intersections	-0.160		-0.125	-0.255	
Accident Location - Bridges/ Underpasses	0.486		0.271	0.507	
Road Alignment - Straight on Hill		0.183	0.213		0.180
Road Alignment - Curve on level		0.136	0.172		0.128
Road Alignment - Curve on Hill		0.118	0.103		0.121

Table 5 – 7: Cont.

Variable	MBL Fatal	MBL Minor	MOL	MML-Fatality Vs NI	MML-Minor Vs NI
Driver Age (years)	0.253	0.053	0.079	0.290	0.080
Driver - Male	0.130	-0.273	-0.161		-0.274
Driver Condition - Normal	-0.831	-0.185	-0.248	-1.036	-0.194
Vehicle Age (years)		0.054	0.050		0.054
Vehicle Type - Vans	0.175	0.110	0.138	0.195	0.106
Vehicle Type - Large Trucks etc	0.041	-0.844	-0.390	-0.093	-0.813
Speed Limit	1.270	0.527	0.529	1.362	0.533
Number of lanes	-0.722	-0.385	-0.411	-0.876	-0.389
RSI		-0.180	-0.149		-0.176
Wind Speed (Km/hr)		-0.068	-0.068		-0.069
Ln(Traffic)	-2.909	-0.765	-1.111	-3.388	-0.784
Collision Based Model					
Freeways	-0.121	0.017	-0.147	-0.106	0.027
Multilane Kings	0.249	-0.039	-0.043	0.230	-0.033
Light/Dawn	-0.230			-0.198	
Week Days	-0.218	-0.102	-0.128	-0.280	-0.101
Road Alignment - Straight on Hill		0.170	0.197		0.158
Road Alignment - Curve on level		-0.004	0.014		-0.008
Road Alignment - Curve on Hill		-0.021	-0.037		-0.014
Weather - Freezing Rain, Snow			-0.081		
Speed Limit	1.190	0.454	0.544	1.275	0.463
Number of lanes	-0.690	-0.345	-0.346	-0.847	-0.348
RSI	0.242			0.235	
Wind Speed (Km/hr)		-0.036	-0.035		-0.037
Ln(Traffic)	-2.412	-0.262	-0.604	-2.542	-0.257

Table 5-8: Prediction Results from Models versus Observed Results – AWCD

Occupant Based Model				
Severity Type	**MBL**	**MML**	**MOL**	**Observed**
No Injury + Minimal Injury	78.3%	77%	80.0%	76.4%
Minor Injury	19.9%	20.5%	17.5%	19.5%
Fatal + Major Injury	1.8%	2.5%	2.5%	4.0%
Vehicle Based Model				
No Injury + Minimal Injury	63.5%	64.3%	69.1%	64.7%
Minor Injury	31.2%	30.4%	27.1%	30.1%
Fatal + Major Injury	5.3%	5.3%	3.8%	5.3%
Collision Based Model				
No Injury + Minimal Injury	55.1%	55.9%	56.9%	53.4%
Minor Injury	40.7%	39.4%	37.9%	40.2%
Fatal + Major Injury	4.2%	4.7%	5.2%	6.5%

5.4.1 Model Comparison

MLwin uses quasi-likelihood for models with discrete dependent variables and thus the reported likelihood estimates are only approximate and could lead to unreliable likelihood ratio tests (Pickery and Loosveldt 2002). As a result, the usual goodness of fit criteria such as AIC and BIC could not be applied (Pickery and Loosveldt 2002). Alternatively, two different measures were used for model comparison. The first measure was to compare predicted collision severity probabilities from the models with observed shares as in **Table 5 - 8**.

Secondly, percent change in elasticities (**Table 5 – 7**) was compared for the models using **Equation 5 - 5**:

$$\Delta E(\%) = \frac{(E_{bm} - E_{tm})}{E_{bm}} * 100 \qquad \textbf{(5 – 5)}$$

where $\Delta E(\%)$ is the percent change in elasticity for a parameter,

E_{bm} is the elasticity value of the parameter for the base model (MML), and

$E_{tm}$is the elasticity value of the parameter for the target model (MOL or MBL).

5.4.1.1 MML versus MOL

Based on the first criteria – model prediction results (**Table 5 – 8**), MML models have a better prediction performance compared to MOL models except for collision based data fatalities where MOL has a slightly better prediction.

In the next step, the percent change in elasticities was calculated for the two models treating MML as the base model. For fatalities and major injuries, percent change in elasticities range from 54% to 76% (average = 62%) for collision data, 29% to 319% (average = 86%) for vehicle data, and 2% to 83% (average = 53%) for occupant data. For minor injuries, these values are 0% to 276% (average = 81%) for collision data, 1% to 52% (average = 21%) for vehicle data, and -1% to 62% (average = 23%) for occupant data. The major difference is observed for fatal and major injury collision for the reason that high severity collisions are low in frequency, whereas ordered logit models require a large amount of data for a reliable estimation (Savolainen and Mannering 2007). For minor injury results, both models are very close for vehicle and occupant based data as compared to collision based data.

5.4.1.2 MML versus MBL

Based on the first criteria – model prediction results (**Table 5 – 8**), MML models have better prediction rates compared to MBL models for occupant and vehicle based data. For collision based data, MBL results are slightly better for No Injury + Minimal injury and Minor injury collisions, whereas for fatality collisions, MML results are closer to the observed severity ratios.

For fatality and major injury collisions, percent change in elasticities range from 3% to 22% (average = 12%) for collision aggregated data, from 3% to 37% (average = 13%) for vehicle aggregated data, and 2% to 33% (average = 12%) for occupant aggregated data. For minor injury collisions, these values are -1% to 51% (average = 14%) for collision aggregated data, 0% to 34% (average = 5%) for vehicle aggregated data, and -1% to 16% (average = 3%) for occupant aggregated data.

Based on the discussion in this section, MML is found to perform better as a whole than MBL and MOL. Results from this model structure will therefore be used for further discussion and analysis of SECD.

5.4.2 Effects of Aggregation and Correlation

If the collision data is used at a disaggregated level such as occupant-based or vehicle-based analysis, then efforts should be made to account for the correlation that exists between occupants in a vehicle or vehicles in a collision such as shown by the variance terms in **Tables 5 – 5 and 5 – 6**. These results show that around 79% of the variation is accounted for at the occupant level, whereas the collision level accounts for 19% of the variation and vehicle level for 2%. This shows that reliability of the modeling results obtained with the multilevel models is higher than those from the single level models.

As previously discussed, data used in a collision level severity analysis are aggregated to the level of collisions. This takes care of the correlation within the data but can result in two immediate problems: 1) loss of information by reducing the number of observations and 2) miss-specification of collision attributes resulting in erroneous share of high severity levels (**Table 5 - 2**). These could result in biased parameter estimates. In this research, we apply the multilevel framework to account for the correlation between occupants of a same vehicle and vehicles of a same collision. Treating occupant based data results as the base case, we can compare modeling results from MML models for the three data sets. The percent change in parameter estimates for fatality and major injury collisions show a difference ranging from -131% to 214% (average reduction in size of the parameter estimate = 13%) between occupant-based and vehicle-based data and -9% to 310% (average reduction in size of the parameter estimate = 62%) between occupant-based and collision-based data. The difference between vehicle-based data (as the base case) and collision-based data is -52% to 191% (average reduction in size of the parameter estimate = 28%). For minor injuries the difference is from -49% to 139% (average reduction in size of the parameter estimate = 20%) between occupant-based and vehicle-based data and from -29% to 134% (average reduction in size of the parameter estimate = 54%) between occupant-based and collision-based data, whereas for vehicle-based data (as the base case) and collision-based data this difference is from -3% to 186% (average reduction in size of the parameter estimate = 64%).

5.5 Modeling of Snow Storm Collisions

As discussed in Section 5.4.1, a MML model was found to have better fit to the data and is therefore used for subsequent analysis of SECD data. Modeling results from the application of MML models to the three levels of aggregation of SECD are given in **Table 5 – 9** whereas **Table 5 – 10** gives their elasticity values.

Table 5-9: Modeling Results for SECD

Categories	Variable	Occupant based Model				Vehicle based Model				Collision based Model			
		Fatality Vs NI		Minor Vs NI		Fatality Vs NI		Minor Vs NI		Fatality Vs NI		Minor Vs NI	
		Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
	Constant	0.464	0.499	0.378	0.336	0.53	0.385	0.102	0.804	1.23	0.001	0.582	0.012
Road Type	Freeways	0.055	0.888	0.048	0.791	0.304	0.361	0.054	0.783	0.12	0.690	0.144	0.458
	Multilane Kings	-0.11	0.815	0.082	0.691	0.037	0.924	0.036	0.873	0.035	0.917	-0.12	0.599
	2 Lane Kings	0.000		0.000		0.000		0.000		0.000		0.000	
Road Related	Road Alignment - Straight on Hill											0.054	0.639
	Road Alignment - Curve on level											-0.03	0.824
	Road Alignment - Curve on Hill											-0.39	0.018
	Road Alignment - Straight on level											0.000	
	Speed Limit			0.01	0.012			0.01	0.012				
	Number of lanes	-0.15	0.000	-0.07	0.000	-0.15	0.000	-0.07	0.000	-0.14	0.000	-0.07	0.000
	RSI			-0.27	0.019			-0.3	0.014				
Other	Collision Location - Intersections	0.862	0.033			0.765	0.034						
	Collision Location - Bridges/ Underpasses	2.162	0.003			1.802	0.002						
	Collision Location - Segment	0.000				0.000							
Weather	Precipitation type (Snow/Freezing Rain)					-0.3	0.056			-0.37	0.012		
	Precipitation type (Otherwise)					0.000				0.000			
Driver	Driver Age (years)	0.01	0.046			0.014	0.005						
	Driver - Male			-0.36	0.000			-0.21	0.003				
	Driver - Female			0.000				0.000					
	Driver Condition - Normal	-0.42	0.031			-0.42	0.021						
	Driver Condition - Other (drinking etc)	0.000				0.000							

Table 5 – 9: Cont.

Categories	Variable	Occupant based Model				Vehicle based Model				Collision based Model			
		Fatality Vs NI		Minor Vs NI		Fatality Vs NI		Minor Vs NI		Fatality Vs NI		Minor Vs NI	
		Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Vehicle	Vehicle Type - Vans			-0.21	0.007			0.118	0.130				
	Vehicle Type - Large Trucks etc			-0.84	0.000			-0.54	0.001				
	Vehicle Type - Car/Station Wagon			0.000				0.000					
Person	Position in Vehicle - Front			0.213	0.009								
	Position in Vehicle - Rear			0.000									
	Safety equipment - Used	-0.69	0.002	-0.77	0.000								
	Safety equipment - Not or bad used	0.000		0.000									
Traffic	Ln(Traffic)	-0.38	0.000	-0.14	0.000	-0.41	0.000	-0.12	0.002	-0.32	0.000	-0.07	0.113
	-2*log likelihood (null):	4505				5010				4401			
	-2*log likelihood (full):	823.5				3404				3495			
	Variance at collision level	0.798				0.228							
	Variance at vehicle level	0				3.29							
	Variance at occupant level	3.29											
	Collision level observations	3035				3035				3035			
	Vehicle level observations	4069				4069							
	Occupant level observations	8081											

Table 5-10: Elasticities of Significant Factors from the Severity Models for SECD

Variable	Occupant Based Model		Vehicle Based Model		Collision Based Model	
	Fatality Vs NI	Minor Vs NI	Fatality Vs NI	Minor Vs NI	Fatality Vs NI	Minor Vs NI
Freeways	0.054	0.047	0.262	0.053	0.113	0.134
Multilane Kings	-0.114	0.079	0.036	0.035	0.034	-0.131
Accident Location - Intersections	0.578		0.535			
Accident Location - Bridges/ Underpasses	0.885		0.835			
Road Alignment - Straight on Hill						0.053
Road Alignment - Curve on level						-0.030
Road Alignment - Curve on Hill						-0.474
Precipitation type (Snow/Freezing Rain)			-0.355		-0.442	
Driver Age (years)	0.376		0.526			
Driver - Male		-0.428		-0.237		
Driver Condition - Normal	-0.525		-0.519			
Vehicle Type - Vans		-0.231		0.111		
Vehicle Type - Large Trucks etc		-1.305		-0.709		
Position in Vehicle - Front		0.192				
Safety equipment - Used	-0.990	-1.162				
Speed Limit		0.737		0.636		
Number of lanes	-0.997	-0.341	-0.977	-0.289	-0.852	-0.236
RSI		-0.127		-0.121		
Ln(Traffic)	-2.864	-0.826	-3.086	-0.626	-2.325	-0.279

5.6 Results

Based on the modeling results provided in the previous section, the following general observations could be made:

- Use of multilevel models is justified because approximately 79% of the variation is accounted for at the occupant level, whereas the collision level accounts for only 19% of the variation, as shown in **Table 5 – 5 and 5 – 6**.

- Aggregation of collision data could result in the misrepresentation of the severity ratios and over or under estimation of the effects of certain factors.
- The modeling results between the two data sets are overall consistent in terms of the factors that were found to have a statistically significant effect on the severity outcome of collisions. The only exception is the effect of collision location (intersection versus segment), which was found to be significant when modeling the snow storm collisions while not so with the all-weather collisions.
- More factors were found to be statistically significant in the severity models for all-weather collision data than those for snow storm collision data (18 versus 12 factors). This can be attributed to the difference in sample size with the all-weather collision data set being five times larger than the snow storm collision data set.
- Most variables are significant in the occupant-based data. The results of the occupant-based model were more reasonable and in-line with the literature.
- In general, the results are consistent with findings from literature, with only a few exceptions.

The following section provides a detailed discussion on the differences between the modeling results from the two data sets using the MML for the occupant-based data as an example.

5.6.1 Traffic Related Factors

- ***Traffic volume***

  Traffic volume is an important factor in not only affecting the frequency of collisions, but also the severity as well. Modeling results from both datasets show that higher traffic volumes are associated with less severe collisions. This could be due to the effect of congestion that may have caused the drivers to lower their speeds. This result is similar to those from literature, e.g., Khattak et al. (1998); Duncan et al. (1998); Klop and Khattak (1999); Khattak (2001); Ulfarsson and Shankar (2003); Kweon and Kockelman (2005); Milton et al (2008) etc.

5.6.2 Vehicle Related Factors

- ***Vehicle Type***

  Modeling results from both datasets shows that heavier vehicles were associated with less severe collisions. This might be due to the incompatibly problem or the capability of the heavy vehicles to absorb the shock generated from the collision impacts more competently than light-weight vehicles. A vehicle incompatibility is defined as "*the combination of its self-protective capacity and aggressivity when involved in collisions with another vehicle*" (Fredette et al. 2008). These results are consistent with those reported by other researchers, such as O'Donnell and Connor (1996); Saccomanno et al (1996); Srinivasan (2002); Wang and Kockelman (2005); Ulfarsson et al (2006); Lenguerrand et al (2006); Fredette et al. (2008) etc.

- ***Vehicle age (years)***

  The modeling results from all-weather collisions indicate that vehicle age is a factor with little influence on the severity of a collision. There was only a slight effect on minor injuries (versus PD), which increases by the age of the involved vehicle. Similar findings were reported by O'Donnell and Connor (1996); Khattak (2001); Wong and Chung (2008) etc.

5.6.3 Road Related Factors

- ***Speed limit***

  Results from both the datasets show that greater speed limits are associated with higher severity levels. This makes intuitive sense as greater impacts are expected from higher speed collisions. Also, less reaction time is available for the driver to adjust to the situation. These effects are consistent with the findings from much of the literature, e.g., O'Donnell and Connor (1996); Khattak et al. (1998); Duncan et al. (1998); Klop and Khattak (1999); Renski et al. (1999); Chang and Mannering (1999); Khattak et al. (2002); Donel and Mason (2004); Dissanayake (2004); Malyshkina and Mannering (2008); Ma and Kockelman (2006); Ma et al (2006), Jung et al. (2010) found that high speed limits were associated with high severity levels. However, a few studies had found that the opposite was true (Qin et al. 2004; Ulfarsson et al. 2006).

- ***Road Alignment***

The results from the all-weather collisions show that collisions occurring on curves are more severe in nature than on straight segments whereas those on grades are severe compared to those on level surface. This result is similar to that obtained by Quddus et al (2010). These factors were not found to be significant in models looking solely at storm only collisions.

- ***Number of Lanes***

Modeling results from both datasets suggest that an increase in number of lanes is associated with less severe collisions. This finding confirms conclusions found in literature such as Khattak (2001); Ma and Kockelman (2006); Kopelias et al (2007). Some studies, however, found that the contrary is also true (e.g. Park and Lord, 2007).

- ***RSI/Road Surface Condition***

Modeling results from the two datasets yielded similar results on the effect of road surface conditions on collision severity. **Figure 5 – 7** shows the change in probability of different severity levels associated with different road surface conditions – RSI, keeping other variables constant. It can be observed that road surface conditions had little correlation with severe collisions and improved road surface conditions slightly reduced the probability of having minor injuries. Similar findings were reported in several past studies (Donel and Mason, 2004; Deng et al, 2006; Mergia, 2010). However, it is in contrast to those from Shankar and Mannering (1996); Khattak et al. (1998); Duncan et al. (1998); Chang and Mannering (1999); Renski et al. (1999); Quddus et al (2002); and Quddus et al (2010) which indicated that poor (wet etc.) road surface conditions were associated with reduced severity levels.

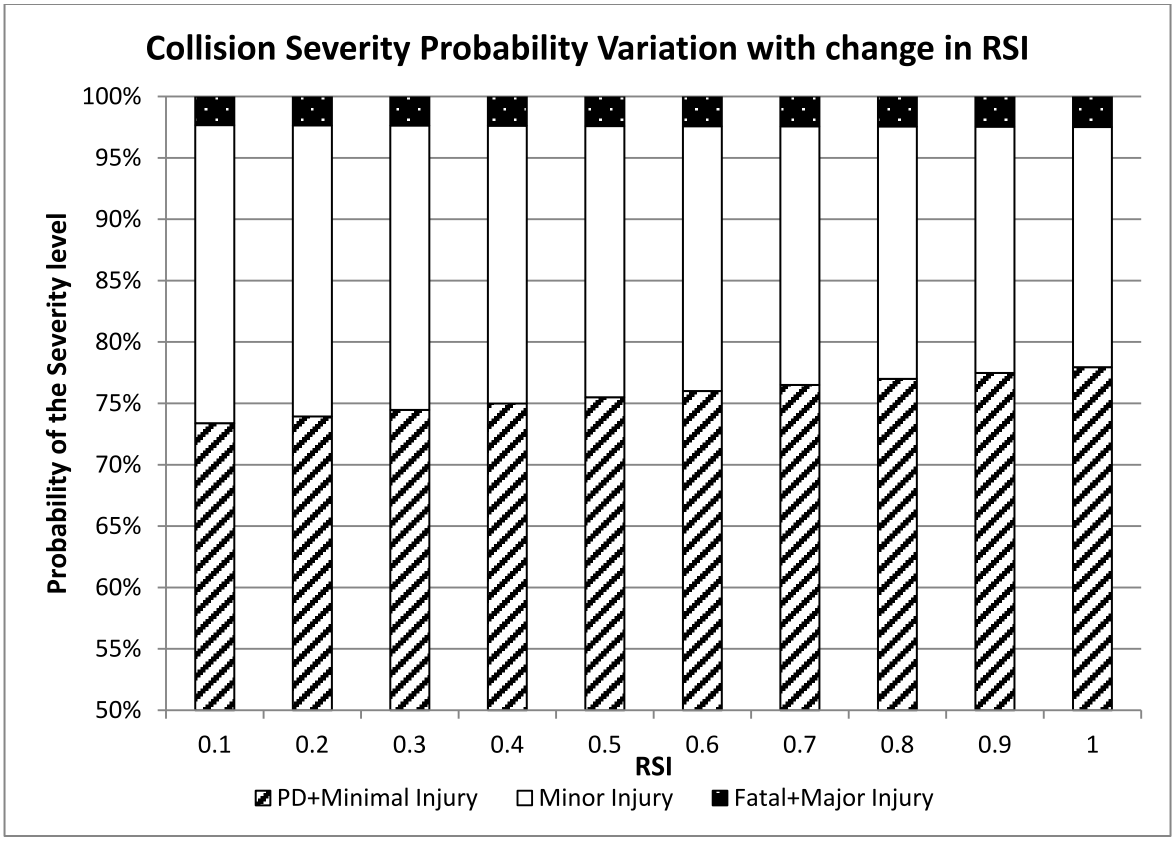

Figure 5-7: Change in collision severity probabilities as a function of RSI

5.6.4 Weather Related Factors

- ***Wind Speed (Km/hr)***

  The modeling results from the all-weather collision data show that higher wind speeds are associated with less severe collisions. Higher wind speeds in winter weather normally are an indication of adverse weather and possible hazardous driving conditions and could cause drivers to be more attentive and possibly reduce their speeds. Khattak et al. (1998) and Jung et al (2010) also found similar results.

- ***Visibility (Km)***

  The modeling results from the all-weather collision data show higher visibilities were found to be associated with less severe collisions. This could be due to the availability of sufficient stopping sight distance for drivers to respond to any collision situations. Saccomanno et al (1996) and Khattak et al. (1998) also found similar results.

5.6.5 Driver Related Factors

- ***Driver Sex***

  Results from both datasets show that the level of severity of a collision is less for male drivers compared to female drivers. This result is consistent with those reported in literature such as, O'Donnell and Connor (1996); Khattak et al. (1998); Duncan et al. (1998); Srinivasan (2002); Jones and Jørgensen (2003); Dissanayake (2004); Wang and Kockelman (2005); Lapparent (2006): Ulfarsson et al (2006); Jung et al. (2010). However, a few other studies have concluded the opposite – a lower proportion of female drivers were involved in severe collisions (Chang and Mannering, 1999; Khattak, 2001; Khattak et al., 2002; and Lenguerrand et al, 2006).

- ***Driver Condition***

  As expected, driving under the effects of alcohol, fatigue etc. increases the chance of experiencing severe collisions. This finding is consistent with those from literature such as, Fridstrøm and Ingebrigtsen (1991); Saccomanno et al (1996); O'Donnell and Connor (1996); Duncan et al. (1998); Renski et al. (1999); Chang and Mannering (1999); Dissanayake and Lu (2002); Khattak et al. (2002); Jones and Jørgensen (2003); Donel and Mason (2004); Dissanayake (2004); Ulfarsson et al (2006).

- ***Driver Age (years)***

  It was found that for a given collision, older drivers have higher chances of collisions. This could be due to the fact that as age increases, the driver's reflexes become less sensitive. This results in reduced vehicle control and a need for longer perception and reaction times. Moreover old age drivers have fragile bodies and thus for a given collision the damage to a young and old driver will be different based on their ability to withstand the shock. These results are similar to those from, e.g., Saccomanno et al (1996); Khattak et al. (1998); Chang and Mannering (1999); Khattak (2001); Khattak et al. (2002); Jones and Jørgensen (2003); Wang and Kockelman (2005); Lapparent (2006); Lenguerrand et al (2006); Ulfarsson et al (2006); and Wong and Chung (2008).

5.6.6 Person Related Factors

- ***Position in Vehicle***

  It was shown that people in front seats have a higher chance of experiencing severe injuries as compared to those in rear seats, as in Saccomanno et al (1996) and Lenguerrand et al (2006).

- ***Safety Equipment Used***

  Use of seat belts was found to reduce collision severities confirming previous results from the literature (Fridstrøm and Ingebrigtsen, 1991; Saccomanno et al 1996; O'Donnell and Connor 1996; Chang and Mannering 1999; Khattak et al. 2002; Yau 2004; Van den Bossche et al 2004; Dissanayake (2004); Wang and Kockelman 2005; Hermans et al 2006b; Lenguerrand et al 2006; Jung et al. 2010 etc.)

5.6.7 Other Factors

- ***Light***

  Presence of adequate lighting was found to be associated with decreases in collision severity (all weather collision data). This could be due to the fact that lighting conditions increase the sight distance of a driver. Several other researchers have found similar results, e.g. Fridstrøm and Ingebrigtsen (1991); Saccomanno et al (1996); Duncan et al. (1998); Chang and Mannering (1999); Klop and Khattak (1999); Khattak (2001); Khattak et al. (2002); Lapparent (2006); Ulfarsson et al (2006); Lenguerrand et al (2006); Wong and Chung (2008).

- ***Collision Location***

  The modeling results show that high proportions of severe collisions had occurred at locations on or near bridges and underpasses as compared to straight segments. These results are similar to those of Mao et al (1997) and Lee and Mannering (1999). The modeling results from the two datasets found contrary results on the effect of intersections. For the all-weather collisions, the severity of a collision is low when it occurres at intersections as compared to straight sections, whereas the opposite was true for the storm collisions. This could be due to drivers failing to manoeuvre safely at intersections during snow storm events.

Lastly, the results of the severity modeling discussed previously bear particular importance with respect to the need to quantify the benefit of winter road maintenance. It has been shown that higher RSI was associated with less severe collisions, which suggests that WRM operations should be expected to be beneficial in reducing the severity of collisions. Furthermore, the varying effects of diverse factors suggest that the impacts of adverse weather could better be understood when both collision frequency and collision severity are considered together. This is because weather related factors have a different degree of impacts on collision frequency and severity, as shown in the previous sections and Chapter 4.

5.7 Application of Severity Models

In order to show the application of the severity models (SECD occupant based MML model), we continue with the examples shown in Section 4.4.1. To use the occupant based severity models in conjunction with collision frequency models, we use an average occupancy factor calculated from the available collision data for the whole province of Ontario as the ratio of total number of people in collisions to total collisions. From the data we have 124,545 people involved in 47,340 collisions, which gives an average occupancy factor of 2.631.

For the base case the average RSI was 0.356 with a mean number of collisions of 1.439. Reduction of BP recovery time to three hours in the first case caused the average RSI to change to 0.375 and the mean number of collisions to 1.214. The total benefit after considering both collision frequency and severity is $14,215 (**Table 5 – 11**), (collision values are taken from Transport Canada, 2008).

In the second case study, it was assumed that some maintenance work has been done in the second hour, improving the average RSI to 0.556 and the mean number of collisions to 0.595. WRM benefits in this case are $53,204 after accounting for collision severities (**Table 5 – 12)**.

Table 5-11: Benefit Analysis of Reduction in BP Recovery Time

	Base Case	Unit Cost of an injury Severity level	Associated Cost (base case)	collisions (BP time reduced)	Collision Cost (BP time reduced)
Mean number of collisions	1.439			1.214	
Number of Occupants	3.786			3.194	
Injury type for the occupants					
PD + Minimal Injury	2.725	249	678.42	2.302	573.14
Minor Injury	1.019	4,674	4,763.68	0.857	4,003.67
Fatal + Major Injury	0.042	2,036,638	86,021.72	0.036	72,672.33
Total Cost			91,463.82		77,249.14

Table 5-12: Benefit Analysis of WRM Operations

	Base Case	Unit Cost of an injury Severity level	Associated Cost (base case)	collisions (with WRM)	Collision Cost (with WRM)
Mean number of collisions	1.439			0.595	
Number of Occupants	3.786			1.565	
Injury type for the occupants					
PD + Minimal Injury	2.725	249	678.42	1.143	284.57
Minor Injury	1.019	4,674	4,763.68	0.405	1,892.38
Fatal + Major Injury	0.042	2,036,638	86,021.72	0.018	36,082.69
Total Cost			91,463.82		38,259.64

5.8 Summary

Three alternative logistic regression models, applied in a multilevel framework, were compared and evaluated for their performance for predicting the conditional probabilities of different severity levels of a given collision. These models were applied to collision data aggregated at three levels – occupant level, vehicle level and collision level. These three levels were used to evaluate the effects of data aggregation and correlation on collision severity analysis. Collision data from six winter seasons (2000 to 2006) containing 13,775 collisions, involving 39,564 individuals and 19,635 vehicles was used for this analysis. Based on the modeling results, it was found that multi-level multinomial logit (MML) has the best overall fit to the data and occupant-based data results are more reliable than vehicle and collision based-data. Similar findings were obtained from an analysis focusing on collisions occurred during snow storm events.

It was found that both data aggregation and within-class correlation affect the parameter estimates from the models. It was also found that factors related to driver (age, sex, action, condition), collision impact location, road (condition, alignment, number of lanes), vehicle (age, type, condition, manoeuvre, number), person (position in vehicle, safety equipment used), weather (precipitation type & intensity, temperature, wind speed, visibility), lighting, speed limit, traffic volume and road surface conditions have statistically significant effects on collision severity outcome. In general, the results indicate that poor weather, good road surface conditions, high traffic volume, young and male drivers, new vehicles and good lighting conditions are associated with reduced severity levels.

Chapter 6
CONCLUSIONS AND FUTURE RESEARCH

In the field of winter road safety most research is directed towards investigation of the effects of weather related factors on safety with little research on the effect of winter road maintenance on winter road safety. The primary objective of this thesis was to conduct an in-depth analysis of the relationship between winter road collision safety, WRM and other factors of interest such as weather conditions and traffic volume. The intent was to develop collision frequency and consequence models that could be used for evaluating the performance of alternative WRM operations using safety as a performance measure. 31 highway sections representing actual WRM patrol routes were selected across Ontario for this investigation. Hourly data on traffic volume, WRM, road surface conditions and weather related variables were obtained from various sources. A systematic statistical analysis was performed on the integrated data set with the objective of relating RSI to winter road safety. This chapter highlights the main contributions of this thesis research with directions for future research.

6.1 Major Contributions

6.1.1 Data Processing

- The major problem that most of the researchers face is unavailability of data. This research has resulted in a comprehensive database covering six winter seasons and 31 sites with data available on hourly basis including variables such as road surface conditions, winter road maintenance, maintenance management information systems, traffic volume, and weather related variables. This data set is currently being used by several other research projects such as road surface condition modeling, mobility impacts of winter snow storms, and development of winter severity index and costing models.

- This research resulted in a comprehensive measure for representing road surface condition – road surface index. This index can be used to map different categorical road surface conditions to a scalar variable. RSI is more flexible to use than the categorical description of road surface conditions.

- This research is the first to create a mechanism for extracting winter storm events. This mechanism accounts for the policy variable – decision about a satisfactory road surface condition at which to consider the end of an event. This mechanism could be used to automate the process of event extraction from datasets on a real time basis.

6.1.2 Accident Frequency Modeling

- This research is among the first to investigate collision frequency under adverse winter conditions, in particular in North America, incorporating the effects of road surface conditions and performing the analysis at very disaggregate levels such as snow storm events and the hours therein. A number of alternative collision prediction models were developed and compared for the relationship between accident frequency and various influencing factors such as traffic volume, weather variables, site and RSI. Different functional forms and effects of different site related variables were tested. The resulting models are expected to have significant implications because of their potential to be applied for quantifying the effects of various factors on snow storm collisions and the benefit of winter road maintenance.

  This research conducted a unique analysis on a data set at two different temporal aggregation levels, namely, event based data (EBD) and hourly based data (HBD). This analysis has two distinct aspects – methodological and practical. From a methodological point of view, results from the analysis of the two datasets show that how temporal aggregation of accident data matters. Data aggregation could result in loss of information and models of distorted effect size. Effect of data correlation (within-event correlation) for the specific data set used in this study was found to be small with inconsequential differences in parameter estimates. One possible reason for this indifference may be the fact that the event level correlation in this data set is weak. Given this, the conventional single-level models may be used for data with weak or no within-event correlation. The use of single-level models for multilevel or hierarchical data with large number of observations can also prove to be time efficient in terms of analysis as multilevel models are normally data intensive and are computationally expensive, requiring much time for analysis (Steenbergen and Jones 2002). In case of high correlation, however, multilevel models should be considered.

From a practical perspective, this approach (EBD and HBD) resulted in models capable of predicting accidents with greater accuracy for a given section of highway under different conditions. EBD models are more useful in quantifying the effect of different maintenance service standards and policies with limited information on weather events and traffic. This knowledge could be sufficient for determining the cost-effectiveness of alternative winter maintenance polices and operations. The aggregate nature of the EBD model makes it a better candidate for evaluating the performance of different patrol routes, contractors etc. On the other hand, HBD models have a higher level of reliability capable of providing more accurate estimates on road accidents. HBD models are useful for determining the optimal time for maintenance treatments as well effects of different treatment operations within an event. This makes the model a better candidate for evaluating different decisions regarding specific events.

- This research was the first to investigate the direct link between road surface conditions and accidents at an operational level. The empirical results have confirmed that road surface condition is in fact one of the most important factors influencing road safety. It has been shown that the developed models can be used to evaluate alternative winter road maintenance policies and operations and assess the safety benefit of a particular winter road maintenance strategy or decision.

- Spatial factors related to individual sites were found to be significant in improving the model fit. If these factors could be regressed against various road and weather related features, it would become possible that the developed models could be generalized and applied to evaluate the risk of other highways in other jurisdictions.

- The safety models developed in this research provide a mechanism to estimate the road safety level based on road surface conditions as well weather and traffic conditions and therefore could potentially be used for generating safety related information for travelers as part of a winter traffic management scheme.

6.1.3 Accident Severity Modeling

- Conventionally, collision data under all weather conditions are considered together in severity analysis, which is appropriate when the goal is to identify the differences in the severity of collisions occurred under normal weather conditions versus adverse weather conditions. This is however not the case for this research. As a result, a different approach was proposed in which only those collisions that had occurred during snow storms were considered in order to determine the relative effect of alternative winter road maintenance decisions (through RSI) for some given snow storm conditions. Alternative severity models for both all-weather collisions and snow storm collisions were developed and compared. The analysis confirmed that these two approaches could result in significantly different conclusions in terms of significance of factors and effect size.

- Most of the past studies on collision severity modeling were conducted at the collision level without accounting for the potential correlation of the severity levels for the vehicles involved in the same collisions or individuals in the same vehicles. This research has applied a multilevel approach to explicitly take into account the hierarchical nature of the data. Data by three levels of aggregation, namely, collisions, vehicles and persons involved, were used to investigate the effects of data aggregation and correlation on modeling results. It was found that models from different data aggregation levels did indeed have significant effect sizes. Moreover data aggregation and correlation were found to cause large differences in parameter estimates.

- Different modeling methodologies are available from literature to examine collision severity as related to various influencing factors; however, little is known on the relative merits of these alternative models. This research conducted an extensive comparative analysis using three most commonly applied logistic model structures– multinomial logit, binary logit and ordered logit. These alternative models were calibrated in a multilevel framework for the three data sets of different aggregation levels and then compared using well-known quality-of-fitness criteria. It was found that multinomial logit provided the best outcome in terms of its fit to the data.

- One of the most important objective of this research is to examine the effect of the average RSI during a storm on the severity of snow storm collisions. It was shown that RSI has a positive effect on reducing the severity of collisions. However, different from its effect on collision frequency, the magnitude of the effect of RSI on severity is less profound. Nevertheless, this finding has further confirmed the need to incorporate the severity component into the cost-benefit analysis of alternative WRM operations.

6.2 Recommendations for Future Research

This section provides a set of recommendations on the possible extensions to this research as follows:

- The current analysis was conducted using data from six winter seasons. In the future research, it would be interesting to incorporate data of more winter seasons so that the stability of these modeling results over time could be assessed.

- This analysis was conducted using data from MTO's Class 1 and 2 highways only. A similar analysis should be conducted on collisions from other classes of highways which usually have different WRM standards.

- The spatial analysis unit considered in this research is highway patrol route, which could be further decomposed into shorter sections with similar geometric features. An analysis on these shorter sections could make it feasible to identify the effects of some geometric features of the highway on winter road safety, such as curvature, grade, and location (e.g., ramps, bridges).

- The main objective of this research was to use safety as a performance measure for evaluating alternative WRM measures. Mobility of a highway such as speed and capacity should also be considered as alternative performance measures. As a result, future research should also focus on investigate the effects of winter weather and road maintenance on mobility related performance measures.

- In this research we have developed prediction models for collision frequency and severity. Prior information about weather related variables could be obtained from weather websites, however, there is still a need to develope models for estimation of traffic volume within a given event or hour during snow storm. Similarly, models could also be developed for road surface condition estimation during snow storm. Such models should be developed and used as inputs to the safety models in this research.

- The multilevel analysis conducted in this research considered random effects of the constant term only. A more complex extension would consider the random effects in the slopes, that is, the slopes could be assumed to vary by events.

- Lastly, future research should be directed to application of the developed models. In this research small case studies were used to demonstrate the applications of the developed models. Future research should apply these models at a larger scale such as at the level of network or a season. Such an analysis could be used to assess the effectiveness of different policies such as reclassification of winter classes.

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Appendix A: Winter Road Maintenance Related Information

Table A –1[7]: Description of Winter Maintenance Operations

Operation Number	Operation Type	Description
7006	Plowing + Salting/Sanding	Combination units when performing dual functions only (Plowing and Salting / Sanding)
7008	Plowing + Pre-wet Salting/Sanding	Combination units when performing dual functions only (Plowing and Pre - wet capable spreaders)
7011	Plowing Only	Using trucks equipped with plow and wing one - way or reversible
7021	Sanding Only	Application of sand on road surface
7023	Pre-wet Sanding	Application of pre-wet sand on the surface of ground
7031	Salting	Application of salt on the surface of ground
7033	Pre-wet Salting	Application of pre-wet salt on the surface of roads
7035	Anti-icing (DLA)	Direct liquid application

Table A –2[8]: MTO Winter Road Maintenance Standards

Level of Service		Highway type and W.A.D.T.	M.A.A.[9] (cm)
Class	Type		
1	Bare Pavement	Multilane divided, and others with W.A.D.T. over 10,000	2.5
2	Bare Pavement	Trans Canada system, and others with W.A.D.T. 2000 – 9999 (South) and 1500 – 9999 (North)	2.5
3	Bare Pavement	1000 – 1999 (South) and 800 – 1499 (North)	4
4	Centre Bare Pavement	500 – 999 (South) and 400 – 799 (North)	5
5	Snow packed	Under 500 (South) and Under 400 (North)	7

[7] Fu et al, 2006
[8] MTO Maintenance Manual, 2003
[9] M.A.A (Maximum allowable accumulation): The maximum depth of snow in cm permitted to accumulate on the road.

Table A –3[10]: Provincial Decision policies for Different Winter Maintenance Operations

	CLASS 1	CLASS 2	CLASS 3	CLASS 4	CLASS 5
WINTER AMINTENANCE – LEVEL OF SERVICE (MQS – 701)					
Primary Objective	Essentially Bare Pavement	Essentially Bare Pavement	Essentially Bare Pavement	Essentially Bare Pavement	Snow Pack
Time to meet Primary Objective A.S.A.P. after the storm, not exceeding:	8 Hrs	16 Hrs	24 Hrs	Centre bare within 24 Hrs. And essentially bare pavement when conditions permit	24 Hrs
WINTER AMINTENANCE – OPERATIONS (MQS – 702 & MBP – 702)					
SALTING Begin salting: -When snow accumulation: -During icy conditions: -Follow up salting:**	< 0.5 cm When required When required	< 0.5 cm When required When required	< 0.5 cm When required When required	< 0.5 cm When required When required	N/A N/A N/A
PLOWING -Begin when accumulation:***	≤ 2.0 cm	≤ 2.0 cm	≤ 2.0 cm	≤ 2.0 cm	≤ 2.0 cm
SANDING -Sand when:****	Slippery Conditions	Slippery Conditions	Slippery Conditions	Slippery Conditions	Slippery Conditions
EQUIPMENT COMPLEMENT CALCULATION (MBP – 703)					
SALTING -Theoretical circuit time:*	1.3 Hrs	1.8 Hrs	2.9 Hrs	4.9 Hrs	N/A
PLOWING -Maximum single lane Km/plow:	55 Km	75 Km	120 Km	206 Km	336 Km
SANDING -Theoretical circuit time:*	N/A	N/A	N/A	N/A	8 Hrs

* Circuit time is the theoretical time required to complete the entire route but does not include the dead head time to return to the point of departure upon completion of the entire route.

** The need for follow up salt will be determined by the precipitation, road conditions and weather.

*** Generally, salt on the road take time to become fully effective and therefore plowing should not normally occur until at least 30 minutes after the salt has been placed, but may occur earlier if warranted due to snow accumulation, ambient temperature, and traffic volume.

**** Sanding should begin as soon as slippery conditions are detected.

[10] MTO Maintenance Manual, 2003

TABLE A – 4[11]: Municipal Classification of Highways

Average Annual Daily Traffic (number of motor vehicles)	**Posted or Statutory Speed Limit (kilometers per hour)**					
	90	**80**	**70**	**60**	**50**	**40**
15,000 or more	1	1	2	2	2	2
12,000 - 14,999	1	1	2	2	3	3
10,000 - 11,999	1	2	2	3	3	3
8,000 - 9,999	1	2	3	3	3	3
6,000 - 7,999	2	2	3	3	3	3
5,000 - 5,999	2	2	3	3	3	3
4,000 - 4,999	2	3	3	3	3	4
3,000 - 3,999	2	3	3	3	4	4
2,000 - 2,999	2	3	3	4	4	4
1,000 - 1,999	3	3	3	4	4	5
500 - 999	3	4	4	4	4	5
200 - 499	3	4	4	5	5	5
50 - 199	3	4	5	5	5	5
0 - 49	3	6	6	6	6	6

TABLE A– 5[12]: Municipal Minimum Maintenance Standards

	SNOW ACCUMULATION		ICY ROADWAYS
Class of Highway	Depth	Time	Time
1	2.5 cm	4 hours	3 hours
2	5 cm	6 hours	4 hours
3	8 cm	12 hours	8 hours
4	8 cm	16 hours	12 hours
5	10 cm	24 hours	16 hours

[11] Municipal Act, 2001, regulation 239/02
[12] Municipal Act, 2001, regulation 239/02

Appendix B: Use of t – Test for Environment Canada Sites Selection

Excel spreadsheet was used to for site selection with the following steps:

1) Null hypothesis : The sites in question have same mean for the weather variable – A (where A was visibility, wind speed, air temperature, precipitation intensity

$$H_0 : \mu_1 - \mu_2 = 0,$$
$$H_1 : \mu_1 - \mu_2 \neq 0$$

2) Calculated t- statistic and degree of freedom as:

$$t_{calc} = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{\left(s_1^2 / n_1\right) + \left(s_2^2 / n_2\right)}}$$

$$\nu = \frac{\left(s_1^2 / n_1 + s_2^2 / n_2\right)^2}{\frac{\left(s_1^2 / n_1\right)^2}{n_1 - 1} + \frac{\left(s_2^2 / n_2\right)^2}{n_2 - 1}}$$

where, n_1 , $\bar{x}_1$, s_1^2 are the sample size (number of observations), mean and standard deviation values of variable – A for site 1 and n_2 , $\bar{x}_2$, s_2^2 for site 2.

3) Compute the critical t – value with α = 0.05 as

$$t_{crit} = t_{\frac{\alpha}{2},\nu}$$

4) When $t_{calc} > t_{crit}$ then null hypothesis was rejected and variable – A dropped from the data set. In case all variables for a far site were different than the near site, then the whole site was dropped.

Appendix C: Regional Site Maps

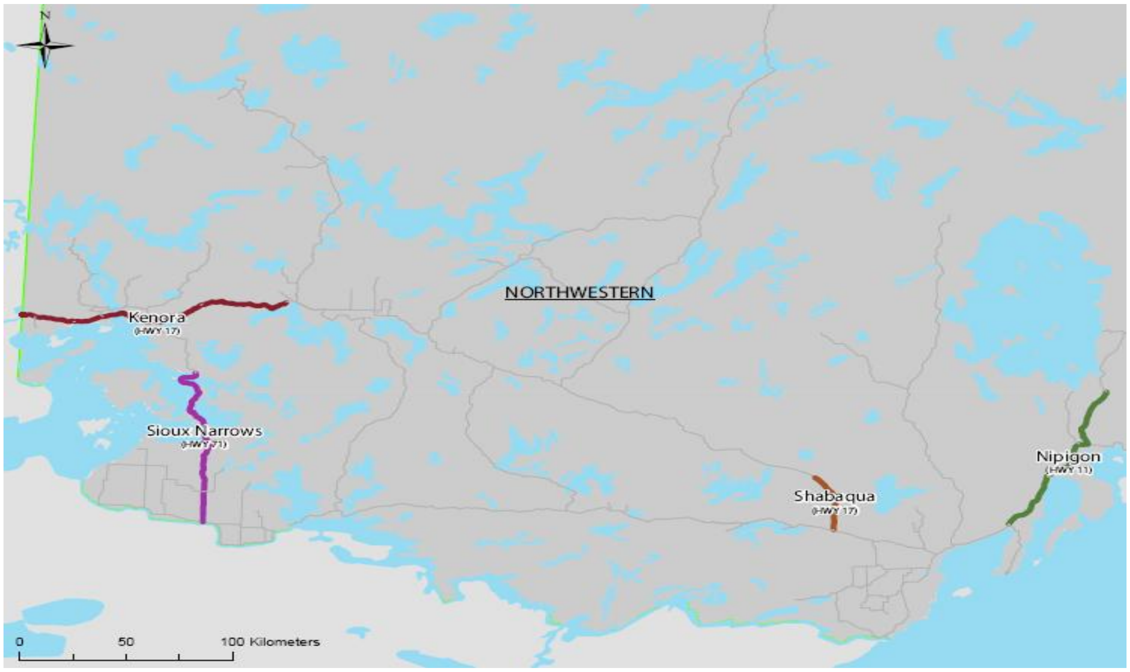


Figure C-1: Patrol routes selected in North-Western region

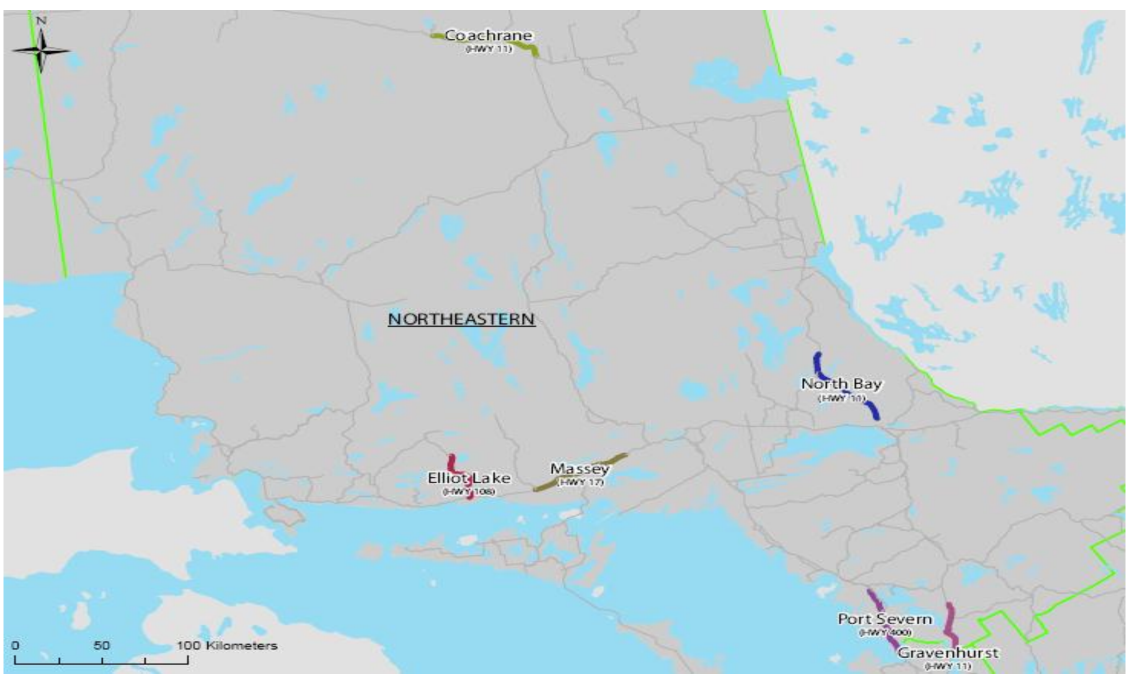


Figure C-2: Patrol routes selected in North-Eastern region

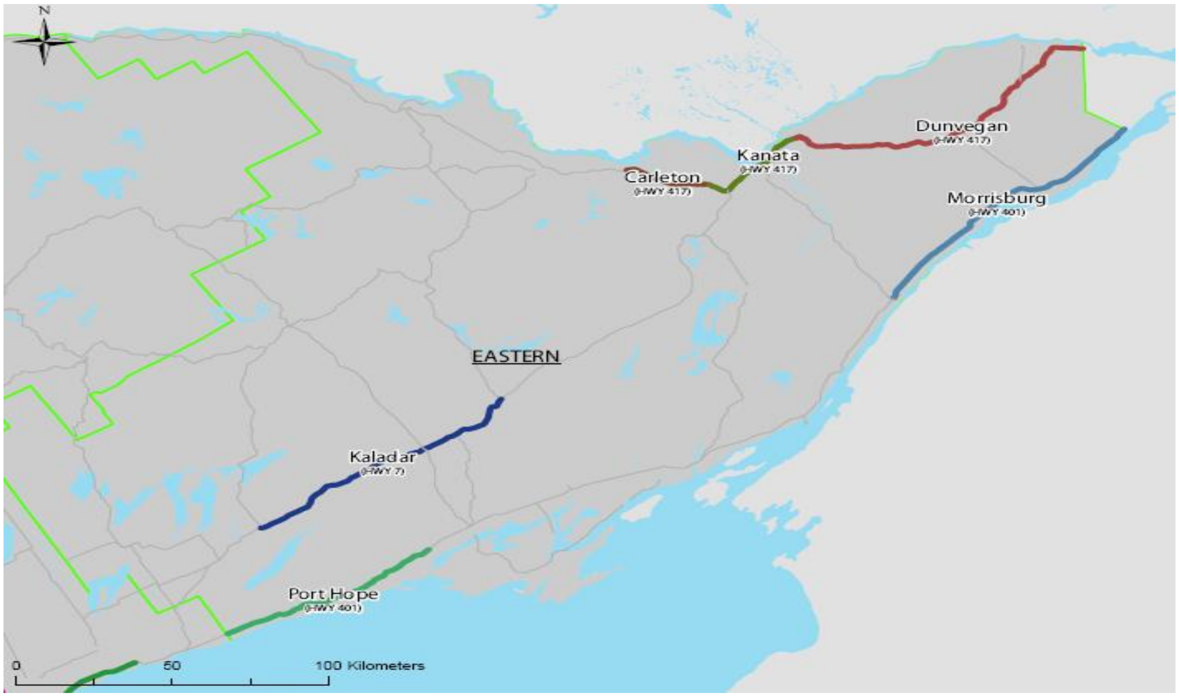


Figure C-3: Patrol routes selected in Eastern region

Figure C-4: Patrol routes selected in Central region

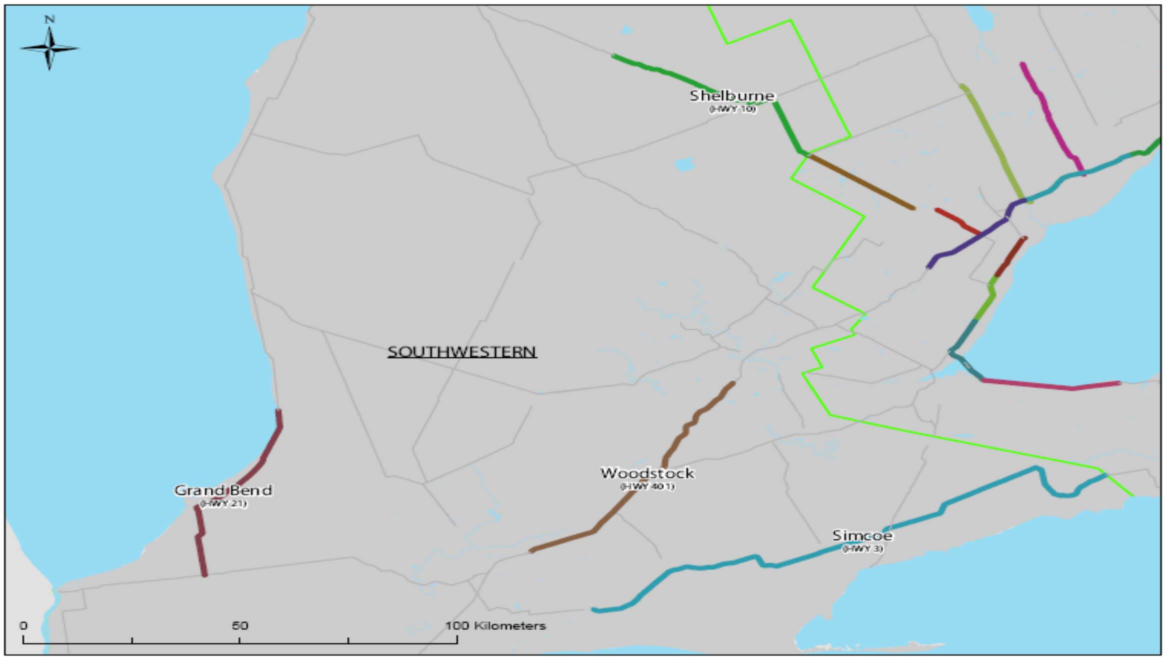


Figure C-5: Patrol routes selected in South-Western region

Appendix D: List of Stations for Different Data Sources Used in the Analysis

Table D-1: List of Permanent Data Count Stations

Hwy No.	PDCS Name	Hwy No.	PDCS Name	Hwy No.	PDCS Name
10	Snelgrove	17	Massey	401	Markham
401	Dixie	11	North Bay	QEW	Burlington
400	Maple	11	Gravenhurst	QEW	Royal Windsor
401	Port Hope	400	Port Severn	QEW	Eastport
401	Keele	11	Nipigon	401	Whitby
401	Liverpool	71	Sioux Narrows	QEW	Oakes Rd
7	Kaladar	17	Kenora	QEW	Ford Dr
417	Dunvegan	21	Grand Bend	QEW	Mississauga
401	Morrisburg	3	Simcoe	401	Milton
417	Ottawa	401	Woodstock	401	Lancaster
11	Cochrane	10	Shelburne	11	Kilkenny
108	Elliot Lake	401	PIA	17	Shabauqua
401	Guelph				

Table D-2: List of RWIS Sites

Arnprior	Grafton	Pearl	Strathroy
BeamsVille	King City	Peel Central	Tower Line
Burlington	Maberly	Peel North	Trenton
Casselman	Marten River	Peel South	Vankleek Hill
Cornwall	Milton	Prescott 401/416	Vemillion Bay
Crooked Bay	Mississauga	Putnam Scale	Walkley
Curry Hill	Morrisburg	Raith	Webbwood
Departure Lake	NewtonVille	RON404	Whitby
Elliot Lake	OrangeVille	Rush Bay	Woodbridge
Etobocoke	Ostrander	Scarborough	
Gorge Creek	Ostryhon Corners	Severn Bridge	
Gormley	Parry Sound	Sioux Narrows	

Table D-3: Environment Canada Stations List for Daily Data

Daily EC Stations			
ALBION	ALLISTON NELSON	MIDDLEPORT TS	ORANGEVILLE MOE
UDORA	GLOUCESTER POOL	MIDLAND HURONIA A	ORILLIA BRAIN
VINELAND	GODFREY	MILLGROVE	OSHAWA WPCP
APPLETON	TORONTO	MOONSTONE	OTTAWA CDA
AURORA NE	CRYSTAL FALLS	GRIMSBY MOUNTAIN	MORRISBURG
AVONMORE	DALHOUSIE MILLS	HAGERSVILLE	MOUNT FOREST
AYLMER	DASHWOOD	HAMILTON A	MOUNTAINVIEW
AYLMER ONT	DORCHESTER	HANOVER	MUSKOKA A
BALDWIN	DRUMMOND	HARTINGTON IHD	MUSKOKA AWOS
BARRIE WPCC	DRYDEN A	HORNBY TRAFALGAR	NAIRN
BARWICK	DRYDEN 'A' (AUT)	ILDERTON BEAR CREEK	NAPANEE
BEATRICE 2	DUNCHURCH	JANETVILLE	NEWMARKET 3
BELLEVILLE	DURHAM	KALADAR	NEWTON
BLACKSTOCK	EGBERT CARE	KAPUSKASING A	NIAGARA FALLS NPCSH
BOLTON NORTH	ELLIOT LAKE A	KAPUSKASING CDA	NILESTOWN
BONNER LAKE	EMO RADBOURNE	KENORA A	NOBLETON
TROUT CREEK	ESSA ONT HYDRO	KING SMOKE TREE	NORTH BAY A
BRANTFORD MOE	EXETER	LAKEHEAD UNIVERSITY	NORTH GOWER
BROCKVILLE PCC	FERGUS MOE	LINDSAY FROST	NORWOOD
WELLAND	FERGUS SHAND	LONDON CS	OAK VALLEY
CALEDON NORTH	FLINT	LONDON INT'L AIRPORT	OAKVILLE GERARD
CAMBORNE	FOLDENS	WARKWORTH	RICHMOND HILL
WATERFORD	FORT FRANCES A	OAKVILLE TWN	ROCKLYN
CARDINAL	FRENCHMANS BAY	OMPAH	ROSEVILLE
CENTREVILLE	GEORGETOWN	OMPAH-SEITZ	RUSKVIEW
COBOURG STP	MADOC	TAPLEY	WOOLER
CONISTON STP	MARKDALE	THEDFORD	ST CATHARINES A
COOKSTOWN	MARSH HILL	THORNHILL	WOODBRIDGE
CORNWALL	MASSEY	THUNDER BAY A	ST THOMAS WPCP
RUSSELL	PORT LAW	STRATTON ROMYN	TORONTO BURNHAMTHORPE
SALEM	PORT PERRY	SARNIA AIRPORT	TORONTO BUTTONVILLE A
SANDFORD	PRICEVILLE	SCOTLAND	TORONTO EAST YORK DUSTAN
SANDHILL	PROTON STATION	SMITHVILLE	TORONTO LESTER B. PEARSON
TRENTON A	RAINY RIVER	WHITBY MUELLER	THUNDER BAY AIRPORT
PARRY SOUND	RAVENSCLIFFE	SPRUCEDALE	OTTAWA MACDONALD-
PETERBOROUGH A	RAWSON LAKE	GLEN HAFFY MONO	OAKVILLE SOUTHEAST WPCP
PETERBOROUGH	THUNDER BAY	WATERLOO WPCP	BURKETON MCLAUGHLIN
WILDER LAKE	THUNDER BAY	STRATHROY-	PETERBOROUGH TORRANCE
PETERBOROUGH	TILLSONBURG MOE	CAMBRIDGE-STEWART	VINELAND RITTENHOUSE
PETROLIA ROKEBY	TILLSONBURG	BOWMANVILLE	SONYA SUNDANCE MEADOWS
PETROLIA TOWN	ST. ALBERT	ALBION FIELD CENTRE	ST CATHARINES POWER GLEN
PONTYPOOL	STIRLING	GRAVENHURST BEAVER	WATERLOO WELLINGTON A
PORT COLBORNE	WOODSTOCK	TORONTO NORTH YORK	

Table D-4: Environment Canada Stations List for Hourly Data

Hourly EC Stations			
CORNWALL	PARRY SOUND CCG	TORONTO ISLAND A	RAWSON LAKE (AUT)
OTTAWA CDA RCS	MOUNT FOREST (AUT)	HAMILTON RBG CS	OTTAWA MACDONALD-CARTIER INT'L A
KAPUSKASING A	SARNIA AIRPORT	WATERLOO WELLINGTON A	REGION OF WATERLOO INT'L AIRPORT
ALEXANDRIA	BEATRICE CLIMATE	WINCHESTER	TORONTO BUTTONVILLE A
ELLIOT LAKE A	HAMILTON A	BROCKVILLE CLIMATE	NORTHERN ONTARIO PORTABLE EMERG WEATHER STN
GODERICH	ST CATHARINES A	KENORA RCS	TORONTO LESTER B. PEARSON INT'L A
BARRIE-ORO	UPSALA (AUT)	PETERBOROUGH A	WELCOME ISLAND (AUT)
BORDEN	SUDBURY A	DRYDEN 'A' (AUT)	TORONTO CITY CENTRE
TRENTON A	FORT FRANCES RCS	DRYDEN A	PETERBOROUGH AWOS
KENORA A	LONDON INT'L AIRPORT	KATATOTA ISLAND (AUT)	KILLARNEY (AUT)
COBOURG (AUT)	MUSKOKA A	TORONTO 407 AND YONGE	THUNDER BAY CS
THUNDER BAY A	KAPUSKASING CDA ON	TORONTO CITY	LITTLE FLATLAND ISLAND (AUT)
ALFRED	GORE BAY AWOS	TORONTO 407 AND MAVIS	BURLINGTON PIERS (AUT)
DELHI CS	LAGOON CITY	MUSKOKA AWOS	ROYAL ISLAND (AUT)
CAMERON FALLS (AUT)	TROWBRIDGE (AUT)	GORE BAY A	PETERBOROUGH TRENT U
NORTH BAY A	VINELAND STATION RCS	SARNIA CLIMATE	
LONDON CS	BORDEN AWOS	KEMPTVILLE CS	
BEAUSOLEIL	WELLAND-PELHAM	MOOSE CREEK	

Appendix E: Data Sample Used in the Analysis

Table E-1: PDCS Sample Data

2010 Channel Summary	Hour	SB Lane 2	SB Lane 1	NB Lane 1	NB Lane 2
Jan 1	00:00	457	54	156	526
Jan 1	01:00	450	56	101	444
Jan 1	02:00	288	40	38	261
Jan 1	03:00	247	27	29	167
Jan 1	04:00	223	26	11	120
Jan 1	05:00	250	34	16	146
Jan 1	06:00	255	46	38	291
Jan 1	07:00	255	31	76	378
Jan 1	08:00	250	28	136	511
Jan 1	09:00	465	138	263	687
Jan 1	10:00	761	339	515	918

Table E-2: RWIS Data Sample

SiteID	DateTime	PTYPE	TEMP	SFC TEMP	PAVE TEMP	ROAD COND	WCHILL	SUBSFC TEMP
RON404	19/06/2007 12:23	noPpt	24.4	27.5			24.4	20.3
RON404	19/06/2007 12:25	noPpt	24.4	27.5			24.4	20.3
RON404	19/06/2007 12:44	noPpt						
RON404	19/06/2007 12:47	noPpt	25.1	28.7			25.1	20.3
RON404	19/06/2007 13:06	noPpt						
RON404	19/06/2007 13:09	noPpt	25.3	29.1			25.3	20.3
RON404	19/06/2007 13:33	noPpt	25.2	28.6			25.2	20.3
RON404	19/06/2007 13:43	noPpt						
RON404	19/06/2007 13:46	noPpt	25.2	28.6			25.2	20.3
RON404	19/06/2007 14:12	noPpt						
RON404	19/06/2007 14:15	noPpt	25.9	31.1			25.9	20.3

Table E-3: Loop Detector Sample Data

VDS :	**401DW0040DES**			Description	W OF MARTIN GROVE		
Hour Ending	25-Dec-00	26-Dec-00	27-Dec-00	28-Dec-00	29-Dec-00	30-Dec-00	31-Dec-00
1:00:00	6442	7044	6426	6332	7228	4362	4570
2:00:00	7358	7200	6537	6482	7104	3816	4864
3:00:00	7144	6974	6455	6605	7210	4862	5038
4:00:00	7225	6896	6838	6674	6902	4294	5119
5:00:00	6482	7064	6484	6557	6926	5018	5300
6:00:00	6820	7026	6318	7086	6982	5118	5310
7:00:00	6774	6948	6748	6856	6978	4928	5358
8:00:00	6640	6828	7010	6456	7030	4702	5432
9:00:00	6036	6952	6506	6675	6506	4574	5412
10:00:00	4594	6090	6905	6896	5672	4508	5362
11:00:00	4552	5782	6762	6891	5650	4650	5634
12:00:00	4188	5848	6248	5864	5266	4450	5850
13:00:00	4088	5848	5882	5450	5344	4658	5805
14:00:00	4090	5468	5470	5060	5300	4146	5316
15:00:00	4484	5116	5018	5130	4984	3873	4888
16:00:00	4738	4912	4116	4417	4606	3178	4524
17:00:00	5104	5212	4408	4232	4392	2950	4054
18:00:00	5684	5124	3894	3807	3926	2642	3558
19:00:00	5620	4982	3944	4214	3889	2808	3310
20:00:00	5504	4690	3832	3669	3614	2712	2746
21:00:00	5118	4027	3532	3514	3536	2842	2580
22:00:00	4604	3356	3382	3088	3246	2470	2374
23:00:00	4046	2654	3102	2940	3298	2666	1900
0:00:00	3092	2192	2696	2478	2542	2454	1218

Table E-4: Accident Data Sample

MVAB.ACIDAT	TIMACI	LHRS	LIGHT	RDSUR	ENV	IMPACT	PERSEX	INJURY
11/01/2000	915	17285	1	4	2	3	M	4
11/01/2000	915	17285	1	4	2	3	F	4
11/01/2000	915	17285	1	4	2	12	M	3
12/01/2000	940	40300	1	6	5	12	F	3
12/01/2000	940	40300	1	6	5	11	M	4
13/01/2000	1345	21120	1	1	1	13	F	4
13/01/2000	1345	21120	1	1	1	13	M	4
13/01/2000	1345	21120	1	1	1	13	M	3
23/01/2000	700	22005	3	6	1	4	F	4

Table E-5: Environment Canada Sample Data

Date	Time	Temperature	Wind Speed	Visibility	Wind Chill	Weather
01/10/1999	00	9.1	9	24.1		Cloudy
01/10/1999	01	9.4	7	24.1		Mostly Cloudy
01/10/1999	02	8.6	13	24.1		Mostly Cloudy
01/10/1999	03	8.7	13	24.1		Mainly Clear
01/10/1999	04	9	9	24.1		Mostly Cloudy
01/10/1999	05	9.2	15	24.1		Rain Showers
01/10/1999	06	9.7	15	32.2		Mostly Cloudy
01/10/1999	07	10.2	13	32.2		Mainly Clear
01/10/1999	08	12	15	32.2		Mainly Clear
01/10/1999	09	14.6	24	40.2		Mostly Cloudy
01/10/1999	10	13.1	22	40.2		Mainly Clear
01/10/1999	11	14.5	30	40.2		Mainly Clear
01/10/1999	12	16.2	30	40.2		Mostly Cloudy
01/10/1999	13	16.3	28	40.2		Mainly Clear
01/10/1999	14	16.2	22	40.2		Mostly Cloudy

Table E-6: RCWIS Data Sample

District	Date	Time	Hwy	From	To	RSC	Ppt	Te mp	Operatio ns
London/Stratfo rd district	28/02/2001	20:56	3	Talbotvill e-royal	St thomas	Bare and dry		-6	
London/Stratfo rd district	28/02/2001	20:56	3	Talbotvill e-royal	Simcoe	Bare and wet with baredry secns	Snow flrrys	-6	
London/Stratfo rd district	28/02/2001	20:56	3	Simcoe	Dunnvill e	Bare and wet with baredry secns	Snow flrrys	-6	Plow, Sand, Salt
Chatham district	28/02/2001	21:07	3	Windsor	Talbotvill e-royal	Bare and dry		-7	
Toronto/Burlin gton district	28/02/2001	21:20	3	Mount carmel	Fort erie	Bare and dry		-6	
Chatham district	01/03/2001	00:14	3	Windsor	Talbotvill e-royal	Bare and dry		-8	
London/Stratfo rd district	01/03/2001	03:11	3	Talbotvill e-royal	Dunnvill e	Bare and dry		-7	
Toronto/Burlin gton district	01/03/2001	03:18	3	Mount carmel	Fort erie	Bare and dry		-7	
Toronto/Burlin gton district	01/03/2001	09:29	3	Mount carmel	Fort erie	Bare and wet		-3	
Chatham district	01/03/2001	13:05	3	Windsor	Talbotvill e-royal	Bare and dry		0	

Appendix F: Descriptive Statistics for Traffic and EC Data

Table F-1: Descriptive Statistics for Traffic data

No	SITES	Highway	Traffic (veh/hr)		
			Min	Max	Average
1	Cochrane	11	1	369	78
2	Dunvegan	417	28	2751	531
3	Elliot Lake	108	1	1860	10
4	Graven Hurst	11	8	4394	697
5	Kaladar	7	1	1900	144
6	Maple	400	274	16307	5253
7	Massey	17	1	753	184
8	Morrisburg	401	16	2886	573
9	North Bay	11	1	743	127
10	Carleton	417	1	520	89
11	Kanata Patrol	417	80	11875	4468
12	Port Hope	401	1	6944	1890
13	Port Severn	400	4	2977	331
14	Snelgrove	10	2	1907	726
15	Grand Bend	21	1	859	150
16	Kenora	17	1	1093	142
17	Nipigon	11	1	471	109
18	Shelburne	10	3	1867	556
19	Simcoe	3	2	1221	254
20	Sioux Narrows	71	1	299	35
21	Shabauqua	17	1	404	93
22	Woodstock	401	84	9364	2260
23	QEW 1	QEW	40	18651	5243
24	QEW 2	QEW	11	9980	3565
25	Highway 410	404	662	14400	6363
26	Hwy 404	410	296	19072	8039
27	Patrol 1	401	5	54189	5530
28	Patrol 2	401	8	59700	7562
29	Patrol 3	401	50	49710	7745
30	Patrol 4	QEW	44	13160	4702
31	Patrol 5	QEW	2	12345	5510

Table F-2: Descriptive Statistics for Environment Canada Data

No	SITES	Highway	Precipitation (cm)			Temperature (C)			Wind Speed (Km/hr)			Visibility (Km)		
			Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg
1	Cochrane	11	0.1	33.1	2.74	-43.75	26.8	-6.84	1	61	13.6	0.2	72.4	19.3
2	Dunvegan	417	0.2	32.4	3.2	-29.84	30.1	-0.95	0.5	57	12.6	0.2	48.3	21.6
3	Elliot Lake	108	0.2	33	4.93	-32.1	24.3	-1.1	1	76	16	0.1	25	12.3
4	Graven Hurst	11	0.1	32.9	4.3	-34.5	27.6	-0.8	0.4	48	12.2	0.1	24.1	13.5
5	Kaladar	7	0.2	28.1	2.82	-30.6	27.5	0.28	0.67	69	12.2	0.2	32.2	19.9
6	Maple	400	0.2	27.2	2.5	-24	30	2.1	0.67	62.67	16.5	0.07	26.43	17.1
7	Massey	17	0.2	33	3.8	-31.5	23.43	-2.16	0.67	61	14.81	0.07	25	18.83
8	Morrisburg	401	0.1	27.2	3.4	-31.75	29.9	-0.98	0.5	61	14.2	0.2	48.3	21.5
9	North Bay	11	0.2	27	3.96	-36.3	27.3	-3.1	0	70	14.42	0.05	24.1	18.37
10	Carleton	417	0.2	31.2	2.86	-30.2	-30.35	-0.93	1	57	13.7	0.2	48.3	21.5
11	Kanata	417	0.2	31.2	2.86	-30.2	30.1	-0.9	0.5	57	12.8	0.2	48.3	21.5
12	Port Hope	401	0.2	21.9	2.7	-29.1	24.1	1.16	1	69.5	14	0.2	32.2	19.9
13	Port Severn	400	0.1	31.0	4.15	-34.8	29.7	-0.28	1	61	9.55	0.2	24.1	20.66
14	Snelgrove	10	0.2	27.4	2.61	-24.6	31.5	1.96	0	76	17.4	0.05	32.2	19.65
15	Grand Bend	21	0.2	22.5	3.26	-25.4	30.46	1.9	0.4	58.67	17.14	0.1	40.2	16.2
16	Kenora	17	0.2	28.6	2.22	-38.5	25.6	-5.5	0.5	57.25	12.6	0.00	27.6	16.84
17	Nipigon	11	0.2	34.5	2.98	-53	23.3	-5.21	1	104	13.66			
18	Shelburne	10	0.2	30.6	3.55	-32.4	28.55	-0.18	1	107	10.74	0	32.2	12.72
19	Simcoe	3	0.1	23.7	2.71	-26.8	28.7	1.65	0.5	51	13.9	0.1	40.2	17.9
20	Sioux	71	0.1	20.6	2.15	-38.7	24.9	-5.2	0.67	60	12.81	0.2	40.2	19.46
21	Shabauqua	17	0.2	44	3.9	-41	24	-4.8	0.67	57	10.8	0.2	48.3	22.66
22	Woodstock	401	0.1	24.4	2.32	-27.4	29.5	1.4	0.5	53.67	13.73	0.1	27.6	15.2
23	QEW 1	QEW	0.2	21.4	2.36	-23.7	30.5	2.2	0.67	54.5	13.55	0.1	40.2	18
24	QEW 2	QEW	0.2	25.9	2.74	-22.8	30.12	2.41	0.4	46.6	14	0.07	48.3	18.5
25	Highway 410	410	0.2	27.2	2.5	-23	30	2.5	0.5	65.5	17.1	0.1	24.1	16.3
26	Hwy 404	404	0.2	27.7	2.6	-24.4	30.8	1.9	0.7	62.5	15.3	0.1	31.2	19.1
27	Patrol 1	401	0.2	27.2	2.4	-26.7	30.7	1.24	1	59	14.2	0.2	40.2	18.5
28	Patrol 2	401	0.2	27.2	2.3	-25.1	31	1.6	0.67	62.5	15.34	0.1	32.15	19.1
29	Patrol 3	401	0.2	26	2.52	-23.5	30	2.4	1.33	70.5	18.45	0.1	25	16.38
30	Patrol 4	QEW	0.2	22.9	2.4	-23.4	30.7	2.5	0.5	54.5	13.6	0.1	24.1	18.92
31	Patrol 5	QEW	0.2	22.9	2.4	-23	30	2.5	0.5	65.5	17.1	0.1	24.1	16.2

Appendix G: Additional References for Effects of Weather on Safety

Table G–1 (Source: Andrey et al, 2001) Additional References for Effects of Weather on Safety.

Reference and Affiliation of First Author	Spatial and Temporal Context of Study	Main Conclusions
Robinson, 1965 (as cited in Maunder, 1970)	Melbourne, Australia	There were 30% more injury collisions during rain.
Rooney, 1967 (Clark University, Department of Geography)	Several USA cities. 1950s through 1960s	This hazard study showed that collisions increased by at least 200% on 3-12 snow days per year.
Campbell, 1971 (Department of Highways, West Virginia)	West Virginia, USA. 1969	Site by site analysis suggests that there are disproportionately more collisions under wet vs. dry conditions.
Orne and Yang, 1972 (Department of Highways, Michigan)	State highways, MI, USA. 1968	Of 8 weather variables examined, the hourly accident rate was affected more by the presence of precipitation than any other variable.
Sabey, 1973 (T.R.R.L.)	Britain. 1969	Injury collisions at nighttime were 20% more frequent under wet vs. dry conditions.
Haghigh-Talab, 1973	2 cities in England. 1966-1967	Accident rates increased during rainfall, especially at night, but the two cities show very different patterns.
T.R.R.L., 1974	Britain. 1972	Injury collisions increased by approximately 50% under snowy or icy, or wet conditions and during fog as compared with clear weather.
Codling, 1974	Britain. 1969-1970	Injury collision rates were approximately 50% higher during rain.
deFreitas, 1975 (University of Queensland, Department of Geography)	5 Canadian cities. 1968-1969	Snow accumulation, mean wind speed and air temperature affected the degree of disruption to society (and the transportation system).
Satterthwaite, 1976 (University College, Traffic Studies Group)	State Highways, CA, USA	Daily accident totals were higher when raining than on clear or cloudy days.
OECD Road Research Group, 1976	Various countries over the globe. Various time spans	4.5 to 21% of Canadian road accidents occur in rain. 15 to 20% of accidents occur when rain is falling in Ireland, the United Kingdom, Germany, France, and Italy. Between 1 and 3% of all accidents occur during fog.
OECD, 1976 (as cited in Perry, 1981)	Britain	The collision rate was twice as high during snow vs. normal conditions.
Roosmark, Anderson and Ahlquist, 1976 (as cited in Smith, 1982a)	Sweden	Collisions were 88% higher on snow vs. non-snow days.
Emanalo, Puustelli, Ciampi and Joshi, 1977 University of Zambia	Zambia, 1954-1974	Traffic casualties decreased by 5% during the rainy season.
Clissold, 1977 Ministry of Transport, New Zealand	New Zealand. 1973	Almost 4 times as many collisions occurred during rain versus dry conditions.
Sherretz and Farhar, 1978 Human Ecology Research Studies	St. Louis area, USA. Summers, 1971-1975	Collisions increased by 1.5 to 3.5 times on rain vs. dry days.
O'Leary, 1978 Wilfrid Laurier University Department of Geography	Kitchener, Canada. 1978	Collisions increased by up to 250% on snow vs. average days.

Table G – 1: Cont.

Reference and Affiliation of First Author	Spatial and Temporal Context of Study	Main Conclusions
National Transportation Safety Board, 1980	United States 1970s	The risk of a fatal accident is 3.9 to 4.5 times greater on wet than on dry pavement. 13.5% of fatal highway accidents occur on wet pavement.
Bertness, 1980 (Illinois State Water Survey)	Chicago area, USA. Summers 1976-1978	On average collisions more than doubled on rain vs. dry days.
Smith, 1982 (University of Strathclyde, Department of Geography)	Glasgow, Scotland. 1978-1979	Collisions increased during precipitation, anywhere from 2% to250% depending on methods employed.
Mende, 1982 (University of Toronto, Department of Engineering)	Metropolitan Toronto, Canada Winter 1980-1981	Significant snowfalls resulted in daily accident rates 1.3 to 2.4 times the average daily rate.
Scott, 1983 (T.R.R.L., Britain)	Great Britain. 1970-1978	Collisions increased during the rain.
Mather, Gossette and Mack, 1983 (University of Delaware, Department of Geography)	Connecticut and South Carolina, USA 1975-1976	On average there were disproportionately more fatal collisions during precipitation.
Jovanis and Delleur, 1983 (North-western University, Department of Engineering)	Indiana toll ways, USA 1987	Collisions increased significantly on snow vs. clear days but there was no significant change on rainy days.
Mercer, 1986 (Counter Attach Program, British Columbia)	British Columbia, Canada. 1984	Weather related traffic accidents constituted 11.1% of total accidents. Of these, it was raining 42% of the time and snowing 19% of the time.
Campbell, 1986 (City of Winnipeg)	Winnipeg, Canada. 1974-1984	Temperatures below -15ºC contribute to greater rates of vehicle collisions than do temperatures between 0 and -15ºC.
Brodsky and Hakkert, 1988 (University of Maryland, Department of Geography)	Israel, 1979-1981. United States, 1983-1984	Rain is responsible for approximately 14% of injury accidents.
Andrey and Olley, 1990 (University of Waterloo, Department of Geography)	Edmonton, Canada. 1983	2% of summer accidents occurred on wet roads, while 40% of winter accidents occur on wet/snowy/icy roads.
Perry and Symons, 1991 (University College, Department of Geography)	Wind storms in England, especially January 1990	Wind storms can result in death, injury and structural damage. Strong winds affect vehicle steering and can cause overturn. Wind can also cause instability in bridges, due to static and dynamic forces.
Pike, 1992 (Meteorological Magazine)	United Kingdom. March 29th, 1986	3 major traffic collisions occurred on motorways when drivers reacted in variable ways to heavy hail showers.
Andrey and Yagar, 1993 (University of Waterloo, Department of Geography)	Calgary and Edmonton, Canada 1979-1983	Collision risk during precipitation increased by 70%.
Edwards, 1994 (University of Wales College, Department of Maritime Studies and International Transport)	England and Wales 1980-1990	The presence of high winds (>22 knots) appeared to double collision risk.
Shankar, Mannering and Barfield, 1995 (University of Washington, Department of Civil Engineering)	I-90 east Seattle, USA. 1988-1993	A 1% increase in the number of rain days resulted in a 0.26% increase in collision frequency. A 1% increase in the number of snow days resulted in a 0.10% increase in collision frequency. There is an interaction between weather and roadway geometrics.

Table G – 1: Cont.

Reference and Affiliation of First Author	Spatial and Temporal Context of Study	Main Conclusions
Levine, Kim and Nitz, 1995 (University of Hawaii, Department of Urban and Regional Planning)	City and County of Honolulu. 1990	For every inch of rainfall, there were approximately 13 more collisions per day.
Lane, McClafferty, Green and Nowak, 1995 (Victoria Hospital and University of Western Ontario)	401 Highway and feeder. Highways near London, Ontario. 1984-1990	8% of fatal accidents and 9% of injury accidents occurred during rain. 12% of fatal accidents and 16% of injury accidents occurred during snow. 13% of fatal crashes and 16% of injury accidents occurred on wet roads, while 13% of fatal accidents and 18% of total injury accidents occurred on snow-covered roads.
Edwards, 1996 (University of Wales College, Faculty of Education)	England and Wales. 1980-1990	In most countries of England and Wales, 4% of road collisions occurred in high winds, 1 to 2% in fog, and less than 1% in snowfall.
Suggett, 1999 (University of Regina, Department of Geography)	Regina, Canada. 1991-1994	Driving during a snow event was twice as likely to result in a crash, and 70% more likely to result in injury. Collision and injury risks were lower for rain than for snow. Periods of elevated risk caused by residual snow lasted up to a week after measurable snow had fallen.
VALT, 2001 (Finland)	Finnish roads. 1999-2000	Benign weather conditions and a very late first snow caused a 30% decrease in winter weather accidents for the year 2000.
Liu, Sharma, Stamatinos and Gerbrandt, 2001 (University of Regina, Department of Engineering)	Saskatchewan. Highway 8. 1993-1997	Accident rates are high in the transition times between summer and winter. Accident frequency is higher in the winter, but overall accident severity is higher in the summer.

Appendix H: Effects of Different Factors on Injury Severity of an Accident

Table H - 1 Effects of Driver Related Factors on Accident Severity

References	Driver Age	Female-Driver	Drinking	Seat belt use	Alcohol level reduced	Position in Vehicle (Front)	Previous Violations/ Fatigue	New drivers/ Gas	Driver	ejection
Fridstrøm and Ingebrigtsen (1991)			+	–				+		
Saccomanno et al (1996)	+		+	–		+			-(Vs passenger)	
Edwards (1998)										
Lee and Mannering (1999)			-(PD only)							
Khattak (2001)	+	–								
Srinivasan (2002)	+	+	+	–			+			
Dissanayake and Lu (2002)		+	+							+
Quddus et al (2002)		+ (Male for PD)								
Jones and Jørgensen (2003)	+	+	+							
Yau (2004)		–		–						
Donel and Mason (2004)			+							
Van den Bossche et al (2004)				–	–					
Dissanayake (2004)		+	+	-						
Wang and Kockelman (2005)	+	+		–		+				
Lapparent (2006)	+	+								
Ulfarsson et al (2006)	+	+	+							
Hermans et al (2006)				–	–					
Lenguerrand et al (2006)	+	–		–		+				
Wong and Chung (2008)	+									
Jung et al (2009)				–						
Jung et al (2010)		+		-						
Number of Studies	**9**	**13**	**9**	**11**	**2**	**3**	**1**	**1**	**1**	**1**
Effect (>50%)	**+**	**+**	**+**	–	–	**+**	**+**	**+**	–	**+**
Effect (>85%)	**+**	**+**	**+**	–	–	**+**	**+**	**+**	–	**+**
Effect (100%)	**+**		**+**	–	–	**+**	**+**	**+**	–	**+**

Table H - 2 Effects of Traffic/Speed Related Factors on Accident Severity

References	Speed Limit	Speed Limit Square	AADT	Speed limit reduced	Deficiency of car following distance	St.Dev of 5 min traffic volume	Average speed	Variance speed peak	Peak 15 min speed	Peak hour speed	Speed change	Ln (Exposur e)
Fridstrøm and Ingebrigtsen (1991)			+ (in terms of exposure)									
Lee and Mannering (1999)	+						- (Sever Injury/ Fatality)					
Khattak (2001)			–									
Dissanayake and Lu (2002)							+					
Ulfarsson and Shankar (2003)			–									
Qin et al. (2004)	–		+									
Donel and Mason (2004)	–		+									
Van den Bossche et al (2004)				–								
Dissanayake (2004)							+					
Kweon and Kockelman (2005)	–	+	–				–	+				
Elvik (2005)											+	
Wang and Kockelman (2005)	+ (- for two vehicle crash)	- (+ for 2 vehicle crash)										
Ulfarsson et al (2006)	–											
Ma et al (2006)	+	– (except fatality and major injury)	+									
Hermans et al (2006)				–								
Park and Lord (2007)			+									
Ma and Kockelman (2006)	+	–										+
Kopelias et al (2007)	–								–	–		
Malyshkina and Mannering (2008)	+											
Milton et al (2008)			+ for PD(- for Injury)									
Jung et al (2009)					–	–						
Jung et al (2010)							+					
Number of Studies	**10**	**4**	**9**	**2**	**1**	**1**	**5**	**1**	**1**	**1**	**1**	**1**
Effect (>50%)	+	–	+	–	–	–	+	+	–	–	+	+
Effect (>85%)				–	–	–		+	–	–	+	+
Effect (100%)				–	–	–		+	–	–	+	+

Table H - 3 Effects of Vehicle Related Factors on Accident Severity

References	Vehicl e Age	Passenge r car	Vehicle weight	Single Vehicle Crash	Impact type	Struck by big vehicle	% of Truck s	Engine capacity	Dynamics	Vehicle condition – No defect	utility pole	Mini Van/ SUV
Saccomanno et al (1996)			–						+	–		
Lee and Mannering (1999)											- (Sever Injury/ Fatality)	
Khattak (2001)	+					+						
Srinivasan (2002)			–		+ (Front Impact)							
Dissanayake and Lu (2002)					+ (for side and front)							
Quddus et al (2002)								+				
Jones and Jørgensen (2003)					+ (head on)							
Yau (2004)	+											
Donel and Mason (2004)					Rear end -Angle - side swipe - Head on (decreased severity order)		+					
Wang and Kockelman (2005)												- (+ for 2 vehicle crash)
Ulfarsson et al (2006)	+	+										
Lenguerrand et al (2006)			–	+	Side - Other - front - Rear (decreasing order)							
Milton et al (2008)							–					
Number of Studies	**3**	**1**	**3**	**1**	**5**	**1**	**2**	**1**	**1**	**1**	**1**	**1**
Effect (>50%)	**+**	**+**	**–**	**+**	**Varies**	**+**		**+**	**+**	**–**	**–**	**–(+)**
Effect (>85%)	**+**	**+**	**–**	**+**		**+**		**+**	**+**	**–**	**–**	**–(+)**
Effect (100%)	**+**	**+**	**–**	**+**		**+**		**+**	**+**	**–**	**–**	**–(+)**

Table H - 4 Effects of Road Related Factors on Accident Severity

References	Road Related Factors						
	Difference of min. and max. shoulder width > 1.22m	**Intersection [Indicator]**	**Segment length**	**Length of section if median width >18.29m**	**Lane Width**	**Broad lane**	**Number of lanes**
Lee and Mannering (1999)		[- (No evident/evident Injury)]				+ (PD only)	
Khattak (2001)							–
Quddus et al (2002)							+
Jones and Jørgensen (2003)		–					
Ulfarsson and Shankar (2003)	+			–			
Qin et al. (2004)			+		– (+ for single vehicle)		
Lapparent (2006)		+					
Ulfarsson et al (2006)							+
Ma et al (2006)					- (except fatality)		
Deng et al (2006)		+			–		
Park and Lord (2007)							+
Ma and Kockelman (2006)							–
Kopelias et al (2007)					–		–
Number of Studies	**1**	**4**	**1**	**1**	**4**	**1**	**6**
Effect (>50%)	**+**		**+**	–	–	–	
Effect (>85%)	**+**		**+**	–	–	–	
Effect (100%)	**+**		**+**	–	–	–	

Table H – 4: Cont.

References	Road Related Factors						
	Urban arterial/{Collector}[/Interstate]	**Shoulder Width**	**Factors for different site**	**Rural area**	**Rural Collector**	**Rural Interstate**	**Mountain or rolling terrain**
Dissanayake and Lu (2002)				+			
Jones and Jørgensen (2003)	[+]			+			
Qin et al. (2004)		– (+ for single vehicle)					
Yau (2004)			Yes				
Kweon and Kockelman (2005)		–		+ (- injury)			+
Ma et al (2006)	+ (except PD)	- (except fatality and major injury)					+ (except fatality and minor injury)
Park and Lord (2007)							+(- fatal)
Ma and Kockelman (2006)	+ {except fatal injury}	– (right side)			+ (except PD and minor injury)	+ (except fatal injury)	+ (Except severe)
Number of Studies	**3**	**4**	**1**	**3**	**1**	**1**	**4**
Effect (>50%)	**+**	–		+	+	+	+
Effect (>85%)	**+**	**–**		+	+	+	**+**
Effect (100%)	**+**	**–**		+	+	+	**+**

Table H – 4: Cont.

References	Road Related Factors						
	Urban arterial/{Collector}[/Interstate]	**Shoulder Width**	**Factors for different site**	**Rural area**	**Rural Collector**	**Rural Interstate**	**Mountain or rolling terrain**
Dissanayake and Lu (2002)				+			
Jones and Jørgensen (2003)	[+]			+			
Qin et al. (2004)		– (+ for single vehicle)					
Yau (2004)			Yes				
Kweon and Kockelman (2005)		–		+ (- injury)			+
Ma et al (2006)	+ (except PD)	- (except fatality and major injury)					+ (except fatality and minor injury)
Park and Lord (2007)							+(- fatal)
Ma and Kockelman (2006)	+ {except fatal injury}	– (right side)			+ (except PD and minor injury)	+ (except fatal injury)	+ (Except severe)
Number of Studies	**3**	**4**	**1**	**3**	**1**	**1**	**4**
Effect (>50%)	**+**	–		+	+	+	+
Effect (>85%)	**+**	**–**		+	+	+	**+**
Effect (100%)	**+**	**–**		+	+	+	**+**

Table H – 4: Cont.

References	Road Related Factors						
	Median width indicator (9.14 to 12.19m)	**Population**	**Median**	**Divided Median**	**Median width**	**Natural median**	**Curb Weight**
Lee and Mannering (1999)				+ (No evident Injury)			
Ulfarsson and Shankar (2003)	+						
Donel and Mason (2004)					–		
Kweon and Kockelman (2005)		+					
Wang and Kockelman (2005)				–		+ (- for two vehicle crash)	+ (- for two vehicle crash)
Ma and Kockelman (2006)			– (except fatal)				
Wong and Chung (2008)			+				
Number of Studies	**1**	**1**	**2**	**2**	**1**	**1**	**1**
Effect (>50%)	+	+			–	+	+
Effect (>85%)	+	+			–	+	+
Effect (100%)	+	+			–	+	+

Table H – 4: Cont.

References	Road Related Factors						
	Sum of combined horizontal and vertical curvature	**Signal type**	**Traffic signal control**	**Vertical grade**	**Curve**	**One way**	**2-way, expressway etc**
Lee and Mannering (1999)					- (PD only)		
Khattak (2001)				+			
Dissanayake and Lu (2002)				+	+		
Quddus et al (2002)					+		+(compare to one way)
Donel and Mason (2004)				+	–		
Wang and Kockelman (2005)				+ (- for two vehicle crash) [effects reversed for downhill]	+	+ (- for two vehicle crash)	
Ulfarsson et al (2006)			+ (- for opposite direction)[opposite effects for age 30-60]	–	+		
Ma et al (2006)				+ (except fatal)			
Deng et al (2006)	+						
Ma and Kockelman (2006)				– (except PD, minor, fatal injury)			
Milton et al (2008)					–		
Wong and Chung (2008)		– Regular, + Flash Vs none					
Jung et al (2009)					+		
Number of Studies	**1**	**1**	**1**	**7**	**8**	**1**	**1**
Effect (>50%)	+	–	+	+	+	+	+
Effect (>85%)	+	–	+			+	+
Effect (100%)	+	–	+			+	+

Table H – 4: Cont.

References	Road Related Factors						
	Number of horizontal curves per kilometre	**Horizontal curve length**	**Degree of curve**	**Vertical curve length**	**Number of interchanges**	**Right turn channel**	**Nearest on ramp**
Ulfarsson and Shankar (2003)	–						
Donel and Mason (2004)					+		
Kweon and Kockelman (2005)		–	+	–			
Ma et al (2006)		+ (except fatal and minor)	+	- (except fatal)			
Park and Lord (2007)						+	
Ma and Kockelman (2006)		–	+	+ (except PD, minor, major injury)			
Kopelias et al (2007)							+
Milton et al (2008)					–		
Number of Studies	**1**	**3**	**3**	**3**	**2**	**1**	**1**
Effect (>50%)	**–**		+			+	+
Effect (>85%)	**–**		+			+	**+**
Effect (100%)	**–**		+			+	**+**
	Number of driveways and minor access	**Main road, motorway etc**	**Access control**	**limited access Indicator**	**Friction if horizontal curve > 0.67/km**		
Edwards (1998)		+					
Ulfarsson and Shankar (2003)					+		
Kweon and Kockelman (2005)		–		–			
Deng et al (2006)	+						
Lenguerrand et al (2006)		+					
Ma and Kockelman (2006)			- (except for PD injury)				
Number of Studies	**1**	**3**	**1**	**1**	**1**		
Effect (>50%)	**+**		**–**	–	+		
Effect (>85%)	**+**		**–**	–	+		
Effect (100%)	**+**		**–**	–	+		

Table H - 5 Effects of Other Factors on Accident Severity

References	Day Light	Afternoon peak/peak hour	Week Ends	Midnight (time)	Maintenance expenditure	Capital cost/Km of County roads	Capital cost/Km of National roads
Fridstrøm and Ingebrigtsen (1991)	–				–	–	+
Saccomanno et al (1996)	–						
Lee and Mannering (1999)		- (No evident Injury)	–	+			
Khattak (2001)	–	–					
Srinivasan (2002)			+				
Dissanayake and Lu (2002)	+ (except fatal injury)						
Quddus et al (2002)			+	+			
Jones and Jørgensen (2003)	–						
Yau (2004)	–	–	+				
Donel and Mason (2004)	–						
Wang and Kockelman (2005)	+ (- for two vehicle crash)						
Lapparent (2006)	–						
Ulfarsson et al (2006)	–		+				
Deng et al (2006)	–						
Lenguerrand et al (2006)	–						
Park and Lord (2007)	+(- for Fatality)						
Wong and Chung (2008)				–			
Jung et al (2009)		–					
Number of Studies	**13**	**4**	**5**	**3**	**1**	**1**	**1**
Effect (>50%)	–	–	+	+	–	–	+
Effect (>85%)	–	–			–	–	+
Effect (100%)		–			–	–	+

Appendix I: Additional Models for Safety Analysis

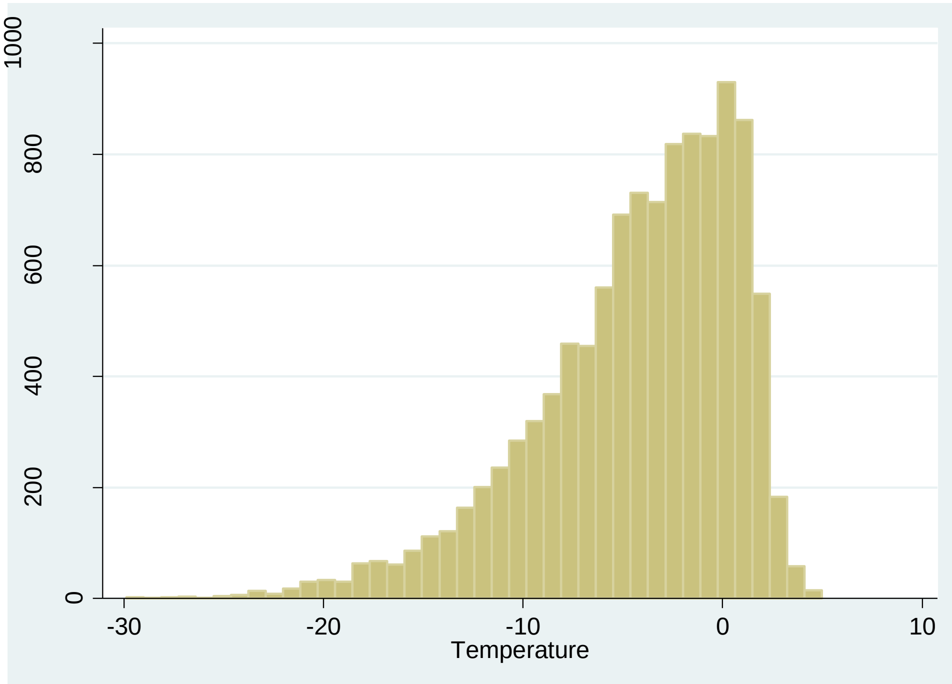
Table I – 1 (Source: Lord and Mannering 2010) Models for Collision Frequency.

Model Type	Previous Research
Generalized estimating equation	Lord and Persaud (2000), Lord et al. (2005a), Halekoh et al. (2006), Wang and Abdel-Aty (2006), and Lord and Mahlawat (2009)
Generalized additive models	Xie and Zhang (2008) and Li et al. (2009)
Random-effects models (Including spatial statistical models)	Johansson (1996), Shankar et al. (1998), Miaou and Lord (2003), Flahaut et al. (2003), MacNab (2004), Noland and Quddus (2004), Miaou et al. (2003), Miaou et al. (2005), Aguero-Valverde and Jovanis (2009), Li et al. (2008), Quddus (2008), Sittikariya and Shankar (2009), Wang et al. (2009) and Guo et al. (2010)
Negative multinomial	Ulfarsson and Shankar (2003), Hauer (2004), and Caliendo et al. (2007)
Random-parameters	Anastasopoulos and Mannering (2009) and El-Basyouny and Sayed (2009b)
Bivariate/multivariate	Miaou and Lord (2003), Miaou and Song (2005), N'Guessan and Langrand (2005a), N'Guessan and Langrand (2005b), Bijleveld (2005), Song et al. (2006), Ma and Kockelman (2006), Park and Lord (2007), N'Guessan et al. (2006), Bonneson and Pratt (2008), Geedipally and Lord (in press), Ma et al. (2008), Depaire et al. (2008), Ye et al. (2009), Aguero-Valverde and Jovanis (2009), El-Basyouny and Sayed (2009a), N'Guessan (2010), and Park et al. (2010)
Finite mixture/Markov switching	Malyshkina et al. (2009), Park and Lord (2009), Malyshkina and Mannering (2010a), and Park et al. (2010)
Duration Models	Jovanis and Chang (1989), Chang and Jovanis (1990), Mannering (1993), and Chung (2010)
Neural network, Bayesian neural network, and support vector machine	Abdelwahab and Abdel-Aty (2002), Chang (2005), Riviere et al. (2006), Xie et al. (2007), and Li et al. (2008)

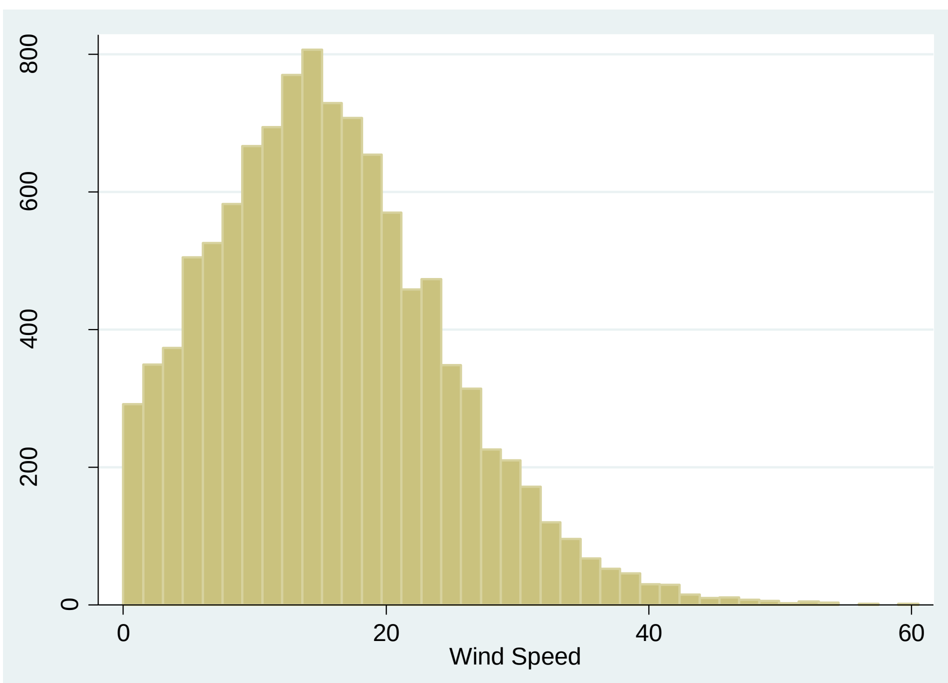
Table I – 2 (Source: Savolainen et al. 2011) Models for Collision Severity.

Methodology	**Previous Research**
Artificial Neural Networks	Delen et al. (2006), Chimba and Sando (2009)
Bayesian Hierarchical	Helai et al. (2008)
Bayesian Ordered Probit	Xie et al. (2009)
Binary Logit and Binary Probit	Shibata and Fukuda (1994), Farmer et al. (1997), Khattak et al. (1998), Krull et al. (2000), Zhang et al. (2000), Al-Ghamdi (2002), Bedard et al. (2002), Toy and Hammitt (2003), Ballasteros et al. (2004), Chang and Yeh (2006), Sze and Wong (2007), Lee and Abdel-Aty (2008), Pai (2008), Rifaat and Tay (2009), Haleem and Abdel-Aty (2010)
Bivariate Binary Probit	Lee and Abdel-Aty (2008)
Bivariate Ordered Probit	Yamamoto and Shankar (2004), de Lapparent (2008)
Classification and Regression	Chang and Wang (2006)
Generalized Ordered Logit	Quddus et al. (2010)
Heterogeneous Outcome	Quddus et al. (2010)
Heteroskedastic Ordered Logit/Probit	O'Donnell and Connor (1996), Wang and Kockelman (2005)
Log-linear Model	Chen and Jovanis (2000)
Markov Switching	Malyshkina and Mannering (2009)
Mixed Generalized Ordered	Eluru et al. (2008)
Mixed Joint Binary Logit-Ordered Logit	Eluru and Bhat (2007)
Multivariate Probit	Winston et al. (2006)
Nested Logit	Shankar et al. (1996), Chang and Mannering (1998), Chang and Mannering (1999), Lee and Mannering (2002), Abdel-Aty and Abdelwahab (2004), Holdridge et al. (2005), Savolainen and Mannering (2007), Haleem and Abdel-Aty (2010)
Partial Proportional Odds	Wang and Abdel-Aty (2008), Wang and Lu (2009), Quddus et
Random Parameters (Mixed) Logit	Milton et al. (2008), Kim et al. (2008), Anastasopoulos and Mannering (2010), Kim et al. (2010), Malyshkina and Mannering (2010), Moore et al. (2010), Ye and Lord (2010a, b), Altwaijri et al. (2011)
Random Parameters (Mixed) Ordered Logit	Srinivasan (2002)
Random Parameters Ordered	Zoi et al. (2010), Paleti et al. (2010)
Sequential Binary Probit	Yamamoto et al. (2008)
Sequential Logit	Jung et al. (2010)
Simultaneous Binary Logit	Ouyang et al. (2002)

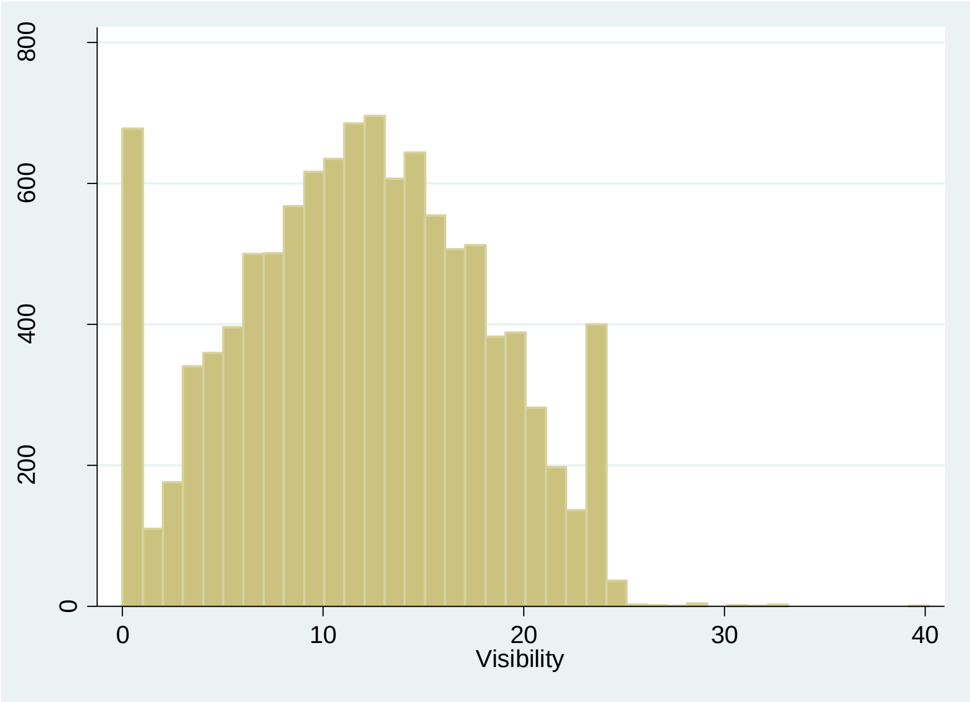
Appendix J: Exploratory Data Analysis Results for EBD



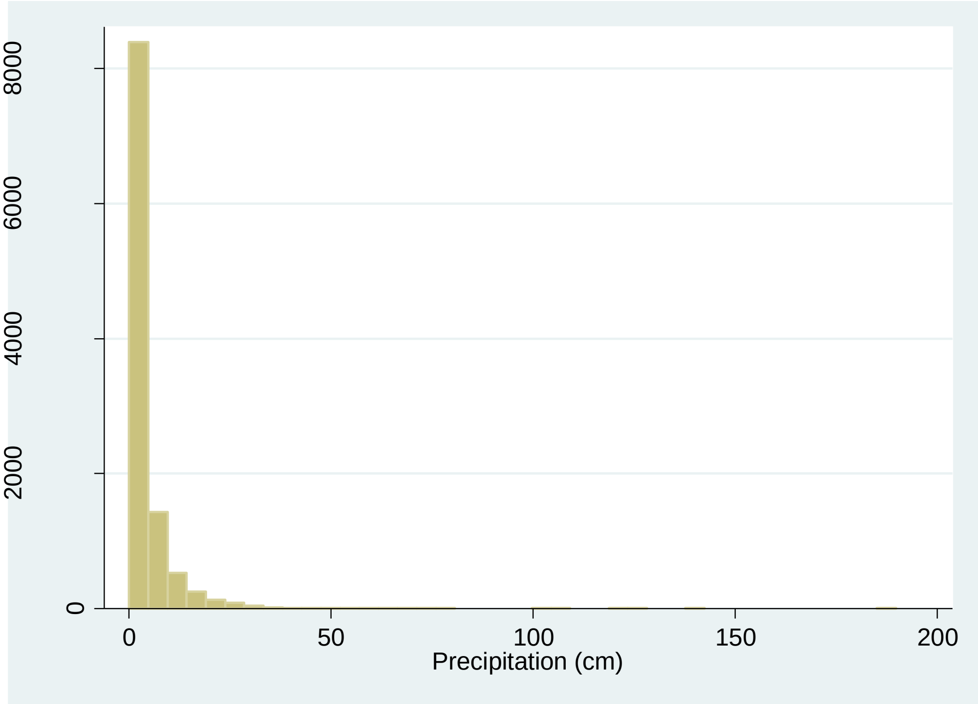
J – 1: Histogram of temperature



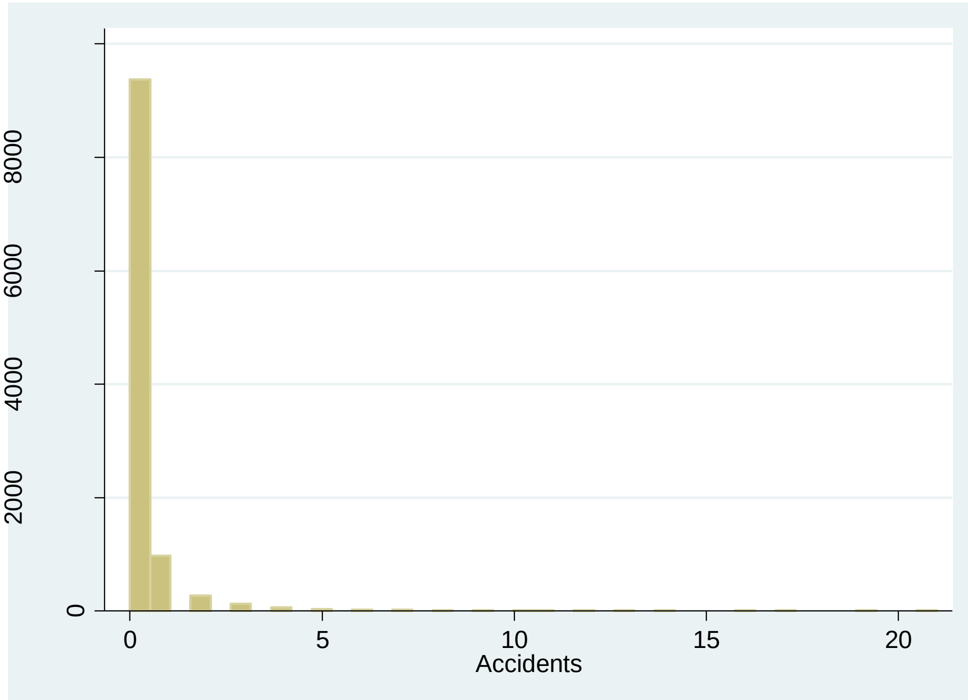
J – 2: Histogram of wind speed



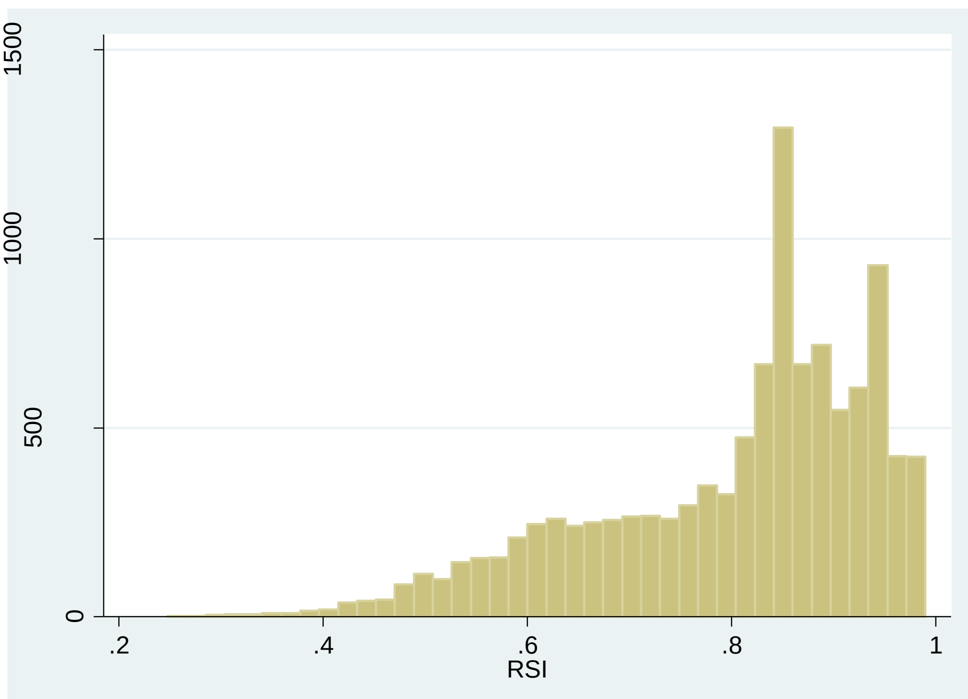
J – 3: Histogram of visibility



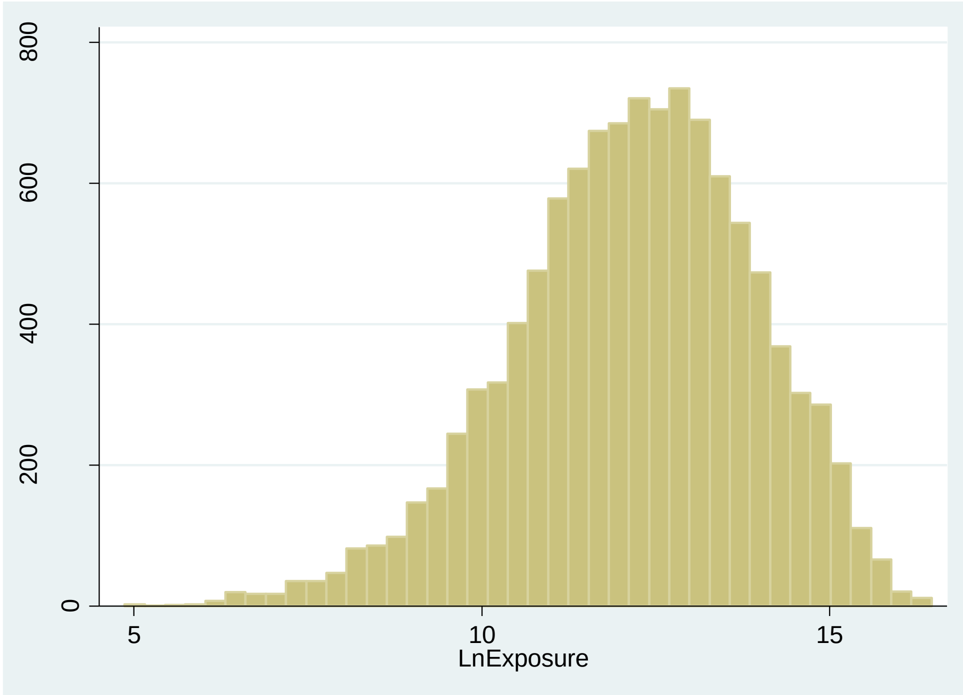
J – 4: Histogram of precipitation



J – 5: Histogram of accidents



J – 6: Histogram of RSI



J – 7: Histogram of exposure

Table J – 1: Descriptive Statistics for EBD – Individual Sites

Site ID		Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation (cm)	Accidents	RSI	Event Duration (hr)	Ln Exposure
Sioux Narrows	Min	-24.55	0.59	1	0.04	0	0.3261	2	6.48
	Max	3.43	35.12	24.1	66	2	0.9877	47	12.18
	Average	-6.8	14.07	12.99	3.55	0.02	0.7848	12.02	10.27
	St.Dev	6.02	6.93	6.05	6.23	0.15	0.1377	9.59	1.05
	N[13]	348	348	348	348	348	348	348	348
Elliot Lake	Min	-21.71	0	0.9	0.1	0	0.4316	2	4.87
	Max	3.6	43	19.55	66.06	2	0.9896	45	11.75
	Average	-4.66	16.47	9.6	6.85	0.02	0.7316	12.36	7.73
	St.Dev	4.75	9.9	3.89	9.6	0.16	0.1411	9.61	0.92
	N	276	276	276	276	276	276	276	276
Grand Bend	Min	-15.98	1.1	1.2	0.04	0	0.381	2	7.6
	Max	3.87	48.82	24.1	68.44	1	0.9896	47	12.8
	Average	-3.43	19.61	13.13	3.94	0.02	0.7442	14.57	10.88
	St.Dev	3.82	7.6	5.54	5.77	0.15	0.1564	11.31	1.06
	N	265	265	265	265	265	265	265	265

[13] N = Number of Observations

Table J – 1: Cont.

Site ID		Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation (cm)	Accidents	RSI	Event Duration (hr)	Ln Exposure
Carleton	Min	-19.73	0	1	0.04	0	0.466	2	8.88
	Max	2.92	42.5	30.18	28.2	2	0.9889	42	13.97
	Average	-4.52	13.53	10.37	3.2	0.02	0.8156	9.2	12.02
	St.Dev	4.59	8.48	5.82	3.94	0.18	0.1201	7.51	0.95
	N	300	300	300	300	300	300	300	300
Shabauqua	Min	-24.16	0.08	1.1	0.12	0	0.4237	2	8.19
	Max	4	32.33	32.2	35.89	1	0.9733	44	11.74
	Average	-6.38	11.21	14.04	5.24	0.02	0.7566	13.17	10
	St.Dev	5.55	6.47	6.54	7.36	0.14	0.147	10.76	0.92
	N	203	203	203	203	203	203	203	203
Cochrane	Min	-29.87	0.19	0.4	0.02	0	0.3554	2	7.31
	Max	3.35	52.94	24.1	189.9	2	0.9896	47	12.41
	Average	-8.81	13.87	14.22	3.83	0.03	0.8112	13.58	10.33
	St.Dev	6.88	7.21	6.23	10.01	0.2	0.1333	11.24	1.08
	N	527	527	527	527	527	527	527	527
North Bay	Min	-23.98	0	0.35	0.04	0	0.429	2	7.33
	Max	3.83	46.17	24.1	125.05	2	0.9897	46	12.43
	Average	-5.44	15.18	11.76	5.28	0.07	0.7806	14.05	10.58
	St.Dev	5.25	7.69	6.09	10.71	0.27	0.1412	10.88	0.99
	N	424	424	424	424	424	424	424	424
Massey	Min	-24.48	0.11	0.63	0.06	0	0.3568	2	8.21
	Max	3.74	47.12	25	140	3	0.99	46	12.93
	Average	-5.53	14.99	12.65	6.39	0.11	0.7711	13.15	11.16
	St.Dev	5.39	8.53	5.18	12.39	0.36	0.141	10.88	1.01
	N	261	261	261	261	261	261	261	261
Nipigon	Min	-27.57	0.13	0	0.04	0	0.3566	2	8.76
	Max	3	35.67	0	29.16	2	0.9881	46	13
	Average	-7.44	11.42	0	3.85	0.09	0.7511	12.96	11.08
	St.Dev	6.31	7.48	0	5.82	0.36	0.1532	10.35	1.02
	N	217	217	217	217	217	217	217	217
Port Severn	Min	-28.42	0	0	0.1	0	0.3061	2	7.8
	Max	4.23	31.5	0	73.1	2	0.9864	46	13.58
	Average	-3.8	8.17	0	5.31	0.07	0.775	10.87	10.99
	St.Dev	4.94	5.58	0	7.27	0.27	0.1363	10.23	1.13
	N	432	432	432	432	432	432	432	432
Graven Hurst	Min	-29.2	1.12	0.95	0.08	0	0.391	2	9.09
	Max	3.55	35.82	24.1	120.75	4	0.9899	47	13.94
	Average	-4.46	14.36	10.1	6.97	0.14	0.7366	13.59	11.88
	St.Dev	4.97	6.6	4.37	9.9	0.44	0.1433	10.41	0.98
	N	388	388	388	388	388	388	388	388

Table J – 1: Cont.

Site ID		Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation (cm)	Accidents	RSI	Event Duration (hr)	Ln Exposure
Kenora	Min	-22.58	0.31	1.71	0.04	0	0.2888	2	8.68
	Max	3.79	31.56	24.1	48.1	3	0.9878	47	13.26
	Average	-6.8	13.07	13.38	3.01	0.1	0.8061	12.6	11.14
	St.Dev	6.01	6.6	4.58	5.63	0.37	0.1379	10.01	1
	N	409	409	409	409	409	409	409	409
Kaladar	Min	-22.34	0	1.4	0.06	0	0.4301	2	8.4
	Max	4.9	44.17	24.1	33.66	1	0.9896	42	13.15
	Average	-3.73	14.39	13.53	3.59	0.07	0.7961	10.66	11.07
	St.Dev	4.62	7.41	6.28	4.69	0.26	0.1236	8.22	0.94
	N	334	334	334	334	334	334	334	334
Snelgrove	Min	-21.6	0	0.8	0.06	0	0.3699	2	8.62
	Max	3.12	60.5	24.1	34.32	2	0.9882	46	13.8
	Average	-3.63	22.4	14.86	4.28	0.07	0.7837	10.42	11.86
	St.Dev	4.12	10.97	6.61	5.57	0.27	0.1338	9.56	0.99
	N	370	370	370	370	370	370	370	370
Simcoe	Min	-23.57	0.38	1.98	0.02	0	0.3563	2	8.7
	Max	4.58	46.34	24.1	70.08	3	0.9896	46	14.23
	Average	-3.59	15.6	13.62	3.58	0.14	0.8068	12.37	12.36
	St.Dev	4.6	7.61	5.52	6.95	0.43	0.1296	9.8	1.03
	N	385	385	385	385	385	385	385	385
Shelburne	Min	-22.5	0	0	0.14	0	0.3481	2	8.14
	Max	3.61	32.5	18.35	71.8	3	0.9899	47	14.11
	Average	-4.27	12.3	11.05	5.44	0.11	0.7397	12.09	11.9
	St.Dev	4.45	6.65	3.79	8.31	0.43	0.1437	10.95	1.12
	N	403	403	403	403	403	403	403	403
Morrisburg	Min	-25.54	0	1	0.08	0	0.4007	2	9.97
	Max	3.35	43.5	40.2	33.79	4	0.9898	42	14.99
	Average	-4.79	14.31	12.16	3.42	0.19	0.8281	8.72	12.86
	St.Dev	4.65	8.82	6.88	4.23	0.5	0.1128	7.27	0.94
	N	329	329	329	329	329	329	329	329
QEW 2	Min	-19.66	0	0.2	0.08	0	0.2943	2	10.35
	Max	4.58	43.52	29.13	51.3	7	0.9897	42	15.49
	Average	-2.99	15.84	13.02	3.22	0.24	0.8449	10.33	13.29
	St.Dev	4.77	7.88	4.87	5.04	0.77	0.1273	7.95	1
	N	321	321	321	321	321	321	321	321
Highway 410	Min	-19.47	2	1.7	0.04	0	0.3996	2	10.65
	Max	4.61	49.31	19.55	29.61	5	0.989	47	14.4
	Average	-2.77	21.99	13.02	2.97	0.14	0.8339	9.78	12.51
	St.Dev	4.01	9.14	4.15	4.08	0.5	0.126	8.29	0.89
	N	370	370	370	370	370	370	370	370

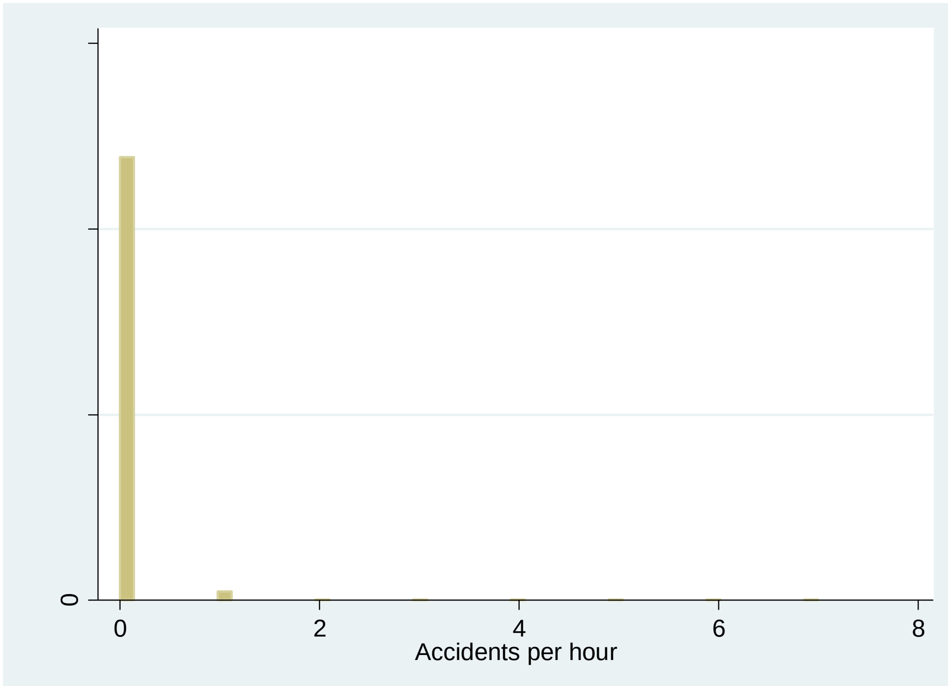
Table J – 1: Cont.

Site ID		Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation (cm)	Accidents	RSI	Event Duration (hr)	Ln Exposure
Dunvegan	Min	-19.81	0.55	0.5	0.08	0	0.4073	2	9.65
	Max	4.45	40	31.4	34.8	3	0.9892	45	15.33
	Average	-4.32	13.29	11.56	3.72	0.23	0.8097	9.23	12.92
	St.Dev	4.77	7.31	6.31	4.65	0.53	0.1225	8.01	1.04
	N	341	341	341	341	341	341	341	341
Port Hope	Min	-20.7	0.18	1.4	0.12	0	0.425	2	11.19
	Max	4.43	53.25	24.1	34.4	14	0.9863	45	16.05
	Average	-2.6	15.55	12.53	3.17	0.66	0.8188	9.74	13.47
	St.Dev	4.02	10.57	5.89	4.09	1.54	0.1202	8.12	0.93
	N	295	295	295	295	295	295	295	295
Patrol 5	Min	-19.75	0	2.08	0.06	0	0.3011	2	9.71
	Max	3.84	50.44	19.55	32.39	5	0.9892	47	14.8
	Average	-2.64	19.8	12.15	2.81	0.16	0.852	9.48	12.55
	St.Dev	3.94	10.57	4.32	4.24	0.56	0.1164	8.54	1.01
	N	315	315	315	315	315	315	315	315
QEW 1	Min	-15.91	2	0.62	0.04	0	0.4167	2	10.88
	Max	4.44	42.67	24.1	28.75	8	0.9899	45	15.79
	Average	-2.72	16.07	11.74	2.73	0.29	0.8679	9.66	13.14
	St.Dev	3.89	7.28	5.23	4.19	0.91	0.1007	8.36	1.01
	N	360	360	360	360	360	360	360	360
Patrol 4	Min	-21.33	0	2.15	0.06	0	0.3133	2	9.83
	Max	4.98	43	24.1	28.38	4	0.9862	45	14.84
	Average	-2.59	14.93	12.17	2.95	0.24	0.8406	8.59	12.58
	St.Dev	3.89	8.21	5.3	4.24	0.6	0.1092	7.73	1
	N	285	285	285	285	285	285	285	285
Kanata Patrol	Min	-19.76	0	1.2	0.04	0	0.4788	2	10.4
	Max	4.45	41.97	32.2	28.2	6	0.9881	42	15.79
	Average	-4.28	15.05	11.16	3.24	0.28	0.8247	9.62	13.6
	St.Dev	4.62	6.65	5.77	4.51	0.69	0.1153	7.81	0.95
	N	369	369	369	369	369	369	369	369
Woodstock	Min	-21.92	1.67	0.68	0.08	0	0.304	2	10.25
	Max	4.7	42.65	24.1	43.23	8	0.9896	45	15.36
	Average	-3.74	16.84	11.45	3.03	0.69	0.8045	12.18	13.37
	St.Dev	4.4	7.41	4.91	4.51	1.39	0.1384	10.31	1.03
	N	409	409	409	409	409	409	409	409
Patrol 1	Min	-19.54	0	0.8	0.04	0	0.3217	2	10.3
	Max	3.1	46	24.1	43.44	10	0.9891	44	16.04
	Average	-3.49	16.42	12.39	2.96	0.47	0.8378	9.39	13.53
	St.Dev	4.27	7.75	6.02	5.17	1.35	0.1121	8.78	1.16
	N	424	424	424	424	424	424	424	424

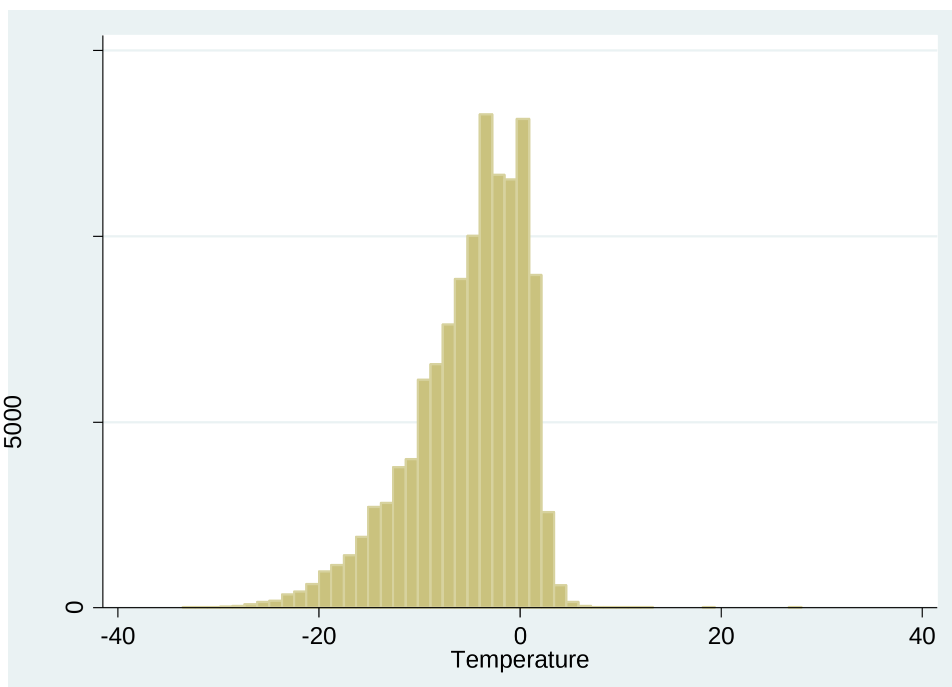
Table J – 1: Cont.

Site ID		Temp. (C)	Wind Speed (Km/hr)	Visibility (Km)	Precipitation (cm)	Accidents	RSI	Event Duration (hr)	Ln Exposure
Hwy 404	Min	-21.38	0	1.6	0.06	0	0.3424	2	12.82
	Max	3.94	47.07	24.1	45.76	11	0.9898	47	16.38
	Average	-3.33	17.54	14.44	3.64	0.51	0.8104	10.25	14.31
	St.Dev	4.5	9.32	5.96	6.01	1.3	0.136	9.2	0.89
	N	401	401	401	401	401	401	401	401
Maple	Min	-20.31	0.65	1.55	0.04	0	0.2956	2	10.73
	Max	4.16	52.23	21.83	105	11	0.9892	46	15.88
	Average	-3.13	19.32	14.39	4.11	0.68	0.7958	11.86	14.05
	St.Dev	4.16	9.82	4.75	9.65	1.46	0.1545	10.27	0.98
	N	382	382	382	382	382	382	382	382
Patrol 3	Min	-20.35	0	1.32	0.05	0	0.2477	2	11.49
	Max	3.55	56.95	19.55	35.25	16	0.9897	47	16.46
	Average	-3.07	21.16	12.61	3.44	0.89	0.8087	10.36	14.02
	St.Dev	4.18	10.74	4.85	5.14	1.9	0.1386	9.6	1.14
	N	351	351	351	351	351	351	351	351
Patrol 2	Min	-24.38	0	1.6	0.04	0	0.2735	2	10.69
	Max	3.94	48.25	24.1	44.94	21	0.989	46	15.92
	Average	-3.38	18.18	13.86	2.55	1.35	0.8308	9.4	13.49
	St.Dev	4.31	9.3	5.83	4.16	2.72	0.1363	8.78	1.08
	N	438	438	438	438	438	438	438	438

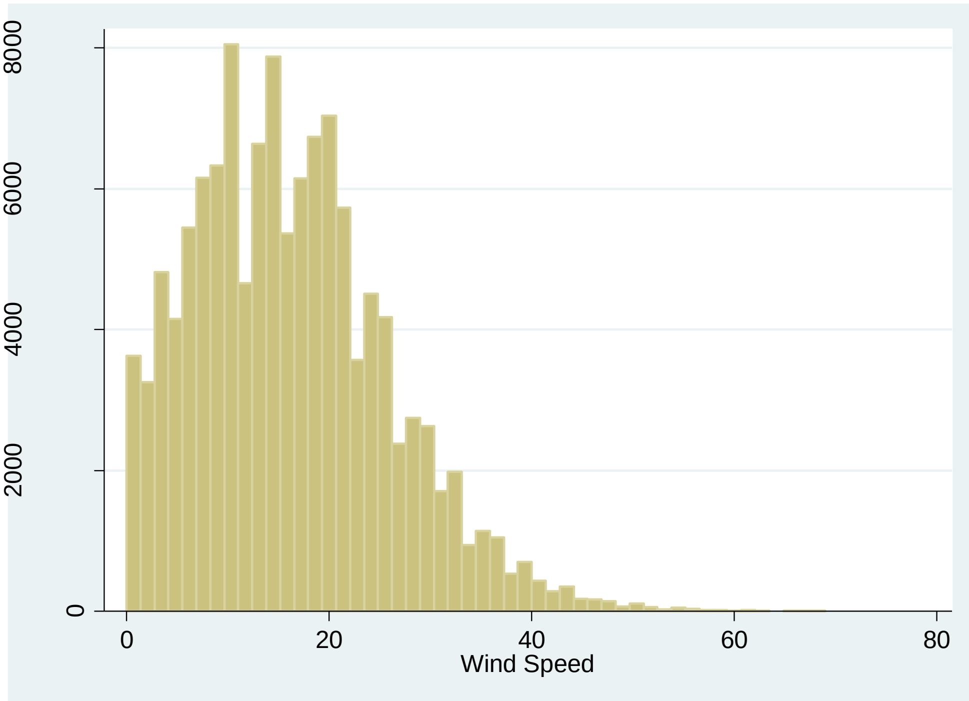
Appendix K: Exploratory Data Analysis Results for HBD



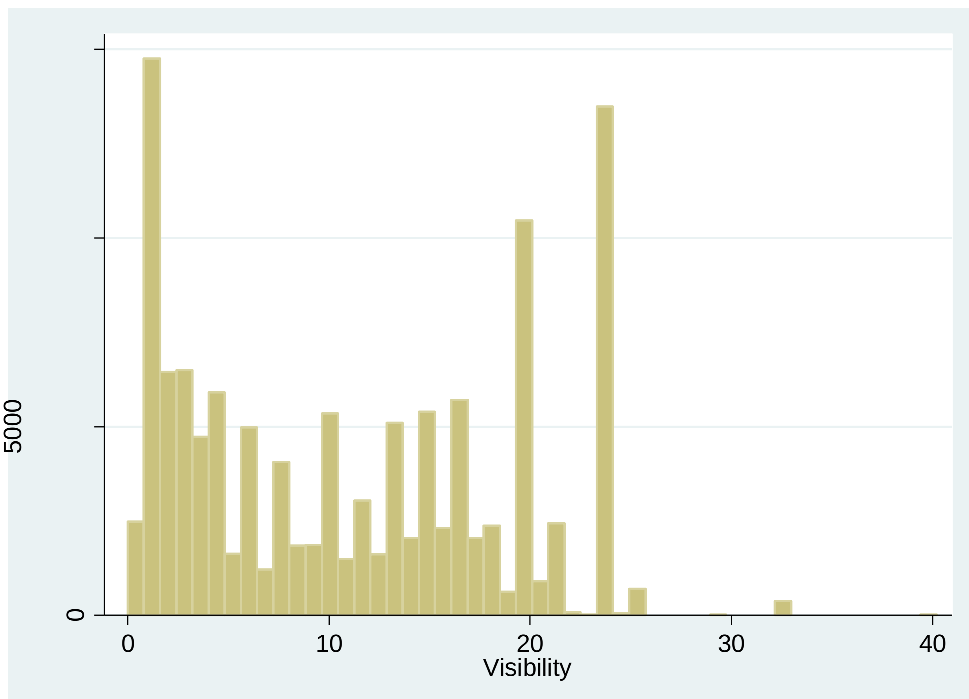
K – 1: Histogram of accidents



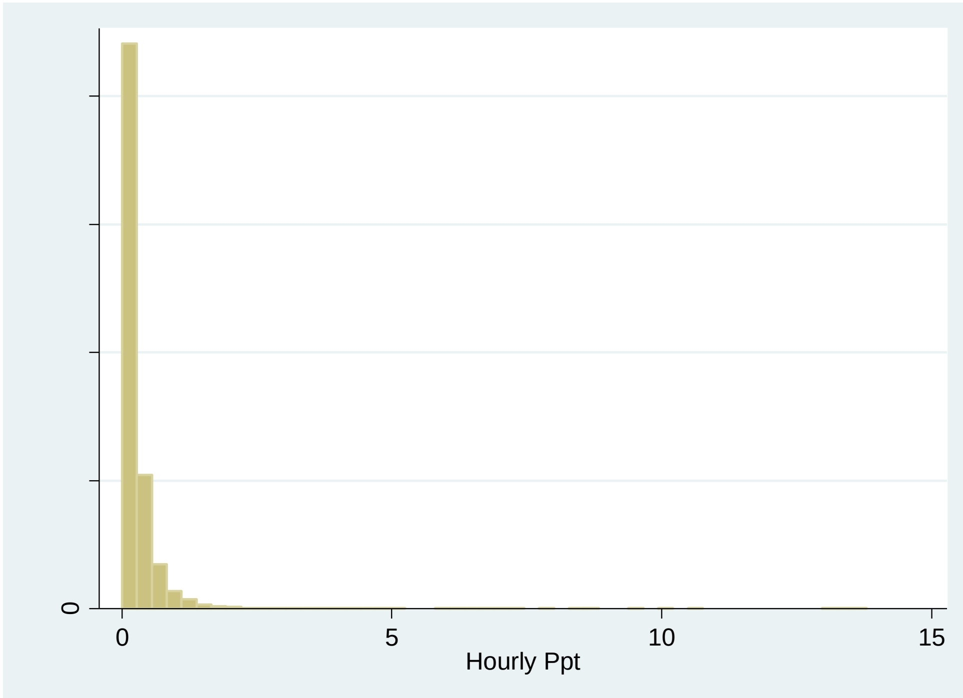
K – 2: Histogram of temperature



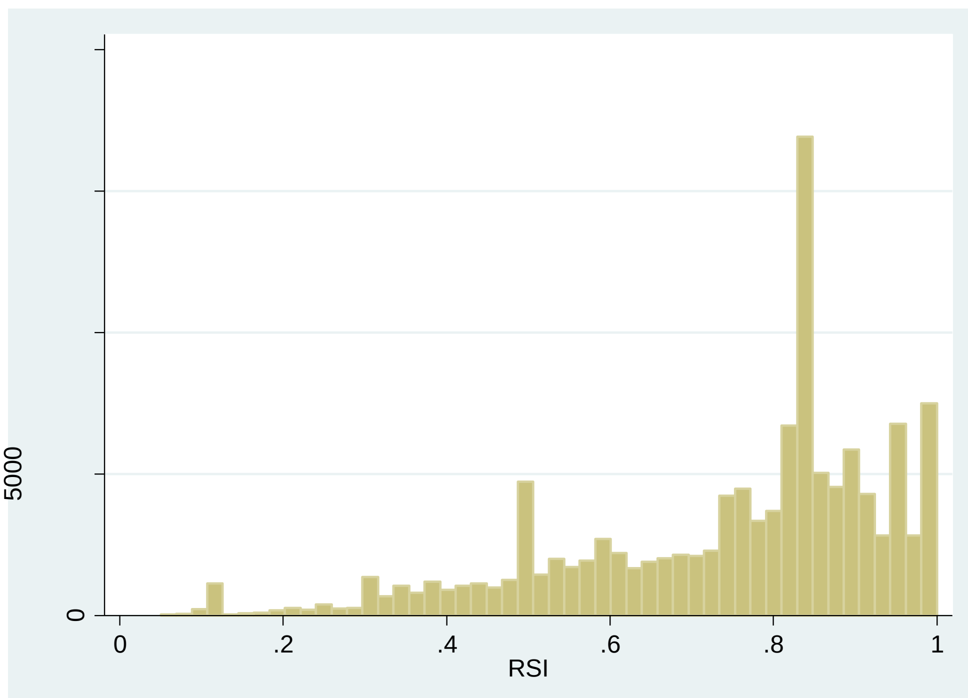
K – 3: Histogram of wind speed



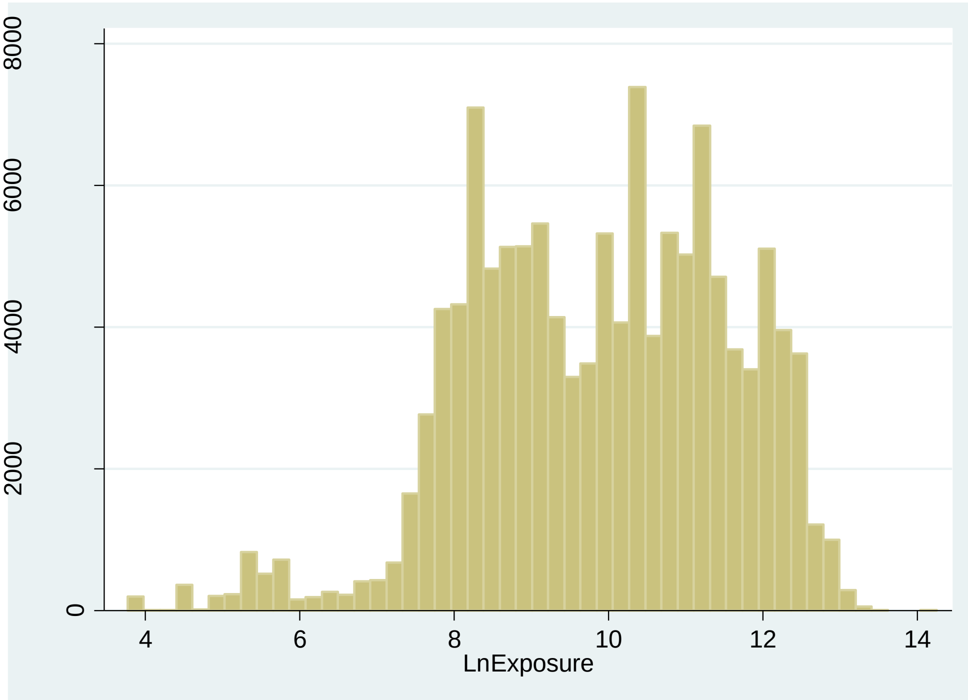
K – 4: Histogram of visibility



K – 5: Histogram of hourly precipitation



K – 6: Histogram of RSI



K – 7: Histogram of exposure

Table K – 1: Descriptive Statistics for HBD – Individual Sites

Site ID		Accidents	Temperature (C)	Wind Speed (Km/hr)	Visibility (Km)	Hourly Ppt (cm)	RSI	Event Duration (hr)	Ln Exposure
Sioux Narrows	Min	0	-27.95	0	0.2	0	0.12	2	4.69
	Max	1	8	44	24.1	9.6	1	47	9.36
	Average	0	-7.54	14.4	12.29	0.16	0.7287	19.66	8.09
	St.Dev	0.04	6.25	7.68	8.78	0.35	0.1809	10.43	0.65
	N	4183	4183	4183	4183	4183	4183	4183	4183
Elliot Lake	Min	0	-27.6	0	0.15	0	0.2014	2	3.77
	Max	1	7.2	57	20	4.4	1	45	11.3
	Average	0	-5.76	17.03	8.9	0.34	0.6645	19.8	5.36
	St.Dev	0.04	5.61	10.95	6.06	0.47	0.1916	11.52	0.66
	N	3411	3411	3411	3411	3411	3411	3411	3411
Grand Bend	Min	0	-25.4	0.27	0.2	0	0.0543	2	4.07
	Max	1	8	56	24.55	4.35	1	47	10.64
	Average	0	-4.16	20.77	12.63	0.17	0.6729	23.31	8.37
	St.Dev	0.04	4.37	9.2	7.85	0.23	0.2154	11.83	0.83
	N	3860	3860	3860	3860	3860	3860	3860	3860
Carleton	Min	0	-21.55	0	0.2	0	0.0888	2	7.27
	Max	1	6	50	32.2	4.57	1	42	11.45
	Average	0	-4.95	14.04	9.62	0.29	0.7858	15.31	9.97
	St.Dev	0.05	4.9	8.83	7.8	0.34	0.1692	9.9	0.69
	N	2761	2761	2761	2761	2761	2761	2761	2761

Table K – 1: Cont.

Site ID		Accidents	Temperature (C)	Wind Speed (Km/hr)	Visibility (Km)	Hourly Ppt (cm)	RSI	Event Duration (hr)	Ln Exposure
Shabauqua	Min	0	-27	0	0.2	0	0.0629	2	7.5
	Max	1	4	46	32.2	6.5	1	44	8.03
	Average	0	-7.11	11.99	12.79	0.25	0.6847	21.92	7.78
	St.Dev	0.04	5.88	7.43	9.68	0.39	0.2058	11.63	0.15
	N	2674	2674	2674	2674	2674	2674	2674	2674
Cochrane	Min	0	-33.55	0	0.2	0	0.106	2	4.22
	Max	1	10	61	24.1	13.8	1	47	9.57
	Average	0	-9.51	15.2	13.67	0.2	0.7682	22.87	8.06
	St.Dev	0.05	7.19	8.37	8.98	0.41	0.184	11.99	0.51
	N	7157	7157	7157	7157	7157	7157	7157	7157
North Bay	Min	0	-27	0	0	0	0.0608	2	5.03
	Max	1	11	65	24.1	7	1	46	10.09
	Average	0	-6.24	16.08	11.29	0.27	0.727	22.46	8.19
	St.Dev	0.07	5.78	8.98	8.83	0.43	0.2003	11.68	0.58
	N	5956	5956	5956	5956	5956	5956	5956	5956
Massey	Min	0	-28	0	0.07	0	0.12	2	6.04
	Max	1	9	53	25	10	1	46	10.26
	Average	0.01	-6.4	16.51	11.7	0.27	0.718	22.11	8.87
	St.Dev	0.09	5.76	8.59	7.35	0.5	0.2046	11.89	0.56
	N	3433	3433	3433	3433	3433	3433	3433	3433
Nipigon	Min	0	-32	0	1	0	0.12	2	7.36
	Max	2	6	46.5	1	6.12	1	46	10.49
	Average	0.01	-8.59	11.72	1	0.17	0.6889	21.19	8.85
	St.Dev	0.09	6.74	8.53	0	0.34	0.2147	10.85	0.48
	N	2813	2813	2813	2813	2813	2813	2813	2813
Port Severn	Min	0	-31.05	0	1	0	0.05	2	6.54
	Max	1	6	58.5	1	9.98	1	46	10.95
	Average	0.01	-4.34	9	1	0.32	0.7207	20.47	8.84
	St.Dev	0.08	5.41	6.75	0	0.48	0.2012	13.05	0.8
	N	4695	4695	4695	4695	4695	4695	4695	4695
Graven Hurst	Min	0	-33.5	0	0.1	0	0.05	2	6.83
	Max	2	6	48	24.1	7.36	1	47	11.36
	Average	0.01	-5.47	14.97	9.18	0.31	0.6731	21.55	9.44
	St.Dev	0.1	5.68	7.9	6.68	0.43	0.1893	11.22	0.69
	N	5272	5272	5272	5272	5272	5272	5272	5272
Kenora	Min	0	-32.13	0	0.2	0	0.05	2	6.6
	Max	2	8	46.75	24.1	4.4	1	47	11.01
	Average	0.01	-7.67	13.99	12.15	0.15	0.7573	20.53	8.86
	St.Dev	0.09	6.4	7.26	6.5	0.27	0.1931	11.27	0.57
	N	5155	5155	5155	5155	5155	5155	5155	5155
Kaladar	Min	0	-26	0.12	0.2	0	0.2071	2	4.59
	Max	1	11	53	24.1	3.74	1	42	11.16
	Average	0.01	-4.3	13.76	12.28	0.26	0.7574	16.97	8.88
	St.Dev	0.08	5.09	7.66	8.65	0.38	0.1854	9.75	0.67
	N	3559	3559	3559	3559	3559	3559	3559	3559

Table K – 1: Cont.

Site ID		Accidents	Temperature (C)	Wind Speed (Km/hr)	Visibility (Km)	Hourly Ppt (cm)	RSI	Event Duration (hr)	Ln Exposure
Snelgrove	Min	0	-26	0	0.2	0	0.0608	2	4.06
	Max	2	10.8	69	24.1	8.7	1	46	10.75
	Average	0.01	-4.26	22.98	14.43	0.25	0.7098	19.16	9.82
	St.Dev	0.09	4.62	12.35	8.73	0.41	0.1947	12.43	0.63
	N	3856	3856	3856	3856	3856	3856	3856	3856
Simcoe	Min	0	-26.8	0	0.1	0	0.0618	2	7.02
	Max	2	28	51	24.1	3.8	1	46	11.39
	Average	0.01	-3.87	16.35	12.71	0.19	0.767	20.12	10.09
	St.Dev	0.11	4.92	8.84	7.28	0.29	0.1949	11.34	0.69
	N	4764	4764	4764	4764	4764	4764	4764	4764
Shelburne	Min	0	-29.35	0	0.08	0	0.0608	2	6.59
	Max	2	11.5	47	24.1	7.18	1	47	11.41
	Average	0.01	-5.05	13.1	10.46	0.24	0.6739	21.98	9.7
	St.Dev	0.1	5.01	7.91	5.48	0.4	0.2027	12.69	0.71
	N	4871	4871	4871	4871	4871	4871	4871	4871
Morrisburg	Min	0	-25.55	0	0.4	0	0.12	2	8.43
	Max	3	5	56	40.2	5	1	42	12.14
	Average	0.02	-5.1	15.33	11.3	0.3	0.7987	14.76	11.01
	St.Dev	0.15	5.05	8.9	8.8	0.38	0.164	9.47	0.48
	N	2868	2868	2868	2868	2868	2868	2868	2868
QEW 2	Min	0	-21.44	0	0.2	0	0.0758	2	6.71
	Max	3	12.5	46.6	29.13	5.13	1	42	12.86
	Average	0.02	-3.47	16.25	12.16	0.25	0.8257	16.42	11.18
	St.Dev	0.16	4.99	8.34	6.51	0.3	0.1684	9.64	0.69
	N	3315	3315	3315	3315	3315	3315	3315	3315
Highway 410	Min	0	-22.5	0.67	0.35	0	0.05	2	9.14
	Max	2	5.52	65.5	24.1	4	1	47	11.98
	Average	0.01	-3.13	22.51	12.52	0.21	0.7862	16.79	10.54
	St.Dev	0.13	4.19	10.37	5.73	0.29	0.1859	10.46	0.34
	N	3619	3619	3619	3619	3619	3619	3619	3619
Dunvegan	Min	0	-24	0.28	0.2	0	0.12	2	8.07
	Max	2	5	46.33	40.2	4.42	1	45	12.5
	Average	0.02	-4.89	13.74	10.97	0.31	0.7655	16.16	11.02
	St.Dev	0.17	5.04	7.39	8.66	0.4	0.1799	10.53	0.64
	N	3146	3146	3146	3146	3146	3146	3146	3146
Port Hope	Min	0	-21.2	0	0.2	0	0.0565	2	8.74
	Max	7	8	67	24.1	6.04	1	45	13.02
	Average	0.07	-3.31	15.35	11.49	0.27	0.7914	16.49	11.43
	St.Dev	0.34	4.45	10.35	8.41	0.37	0.1965	10.81	0.59
	N	2872	2872	2872	2872	2872	2872	2872	2872
Patrol 5	Min	0	-22	0	0.35	0	0.05	2	8.34
	Max	3	12	65.5	19.55	2.94	1	47	11.93
	Average	0.02	-3.12	21.23	11.34	0.23	0.8253	17.15	10.57
	St.Dev	0.15	4.25	11.43	5.86	0.3	0.1624	11.48	0.67
	N	2986	2986	2986	2986	2986	2986	2986	2986

Table K – 1: Cont.

Site ID		Accidents	Temperature (C)	Wind Speed (Km/hr)	Visibility (Km)	Hourly Ppt (cm)	RSI	Event Duration (hr)	Ln Exposure
QEW 1	Min	0	-19.63	0.67	0.2	0	0.0629	2	6.72
	Max	5	12.5	48.67	24.1	4.84	1	45	12.87
	Average	0.03	-3.28	16.83	11.03	0.23	0.8292	16.87	11.14
	St.Dev	0.21	4.21	8.54	6.98	0.34	0.1517	11.11	0.69
	N	3477	3477	3477	3477	3477	3477	3477	3477
Patrol 4	Min	0	-22	0	0.4	0	0.0629	2	8.47
	Max	3	12	45	24.1	3.63	1	45	12.05
	Average	0.03	-2.97	15.59	11.28	0.27	0.7965	15.52	10.68
	St.Dev	0.18	3.99	8.94	6.76	0.34	0.1637	10.74	0.68
	N	2449	2449	2449	2449	2449	2449	2449	2449
Kanata Patrol	Min	0	-24	0	0.2	0	0.12	2	8.81
	Max	3	5.25	46.33	40.2	13	1	42	13.02
	Average	0.03	-4.78	14.71	10.42	0.27	0.7816	15.93	11.51
	St.Dev	0.19	4.95	7.34	8.41	0.38	0.1597	9.87	0.7
	N	3548	3548	3548	3548	3548	3548	3548	3548
Woodstock	Min	0	-25.9	0.5	0.1	0	0.0622	2	9
	Max	5	5.9	52.5	24.1	4.15	1	45	12.58
	Average	0.06	-4.4	17.9	11.12	0.18	0.7464	20.89	11.17
	St.Dev	0.28	4.78	8.48	6.64	0.24	0.2017	11.48	0.62
	N	4982	4982	4982	4982	4982	4982	4982	4982
Patrol 1	Min	0	-24	0	0.2	0	0.0715	2	9.46
	Max	4	6.1	59	24.1	6.17	1	44	13.24
	Average	0.05	-4.4	15.65	11.68	0.21	0.7723	17.57	11.55
	St.Dev	0.26	4.85	9.09	8.1	0.33	0.1734	11.67	0.86
	N	3983	3983	3983	3983	3983	3983	3983	3983
Hwy 404	Min	0	-24.43	0	0.1	0	0.0629	2	12.12
	Max	3	7.07	58	24.1	6.29	1	47	12.54
	Average	0.05	-4.18	17.64	13.3	0.23	0.7448	18.48	12.36
	St.Dev	0.24	4.93	10.28	7.76	0.35	0.2172	11.69	0.11
	N	4109	4109	4109	4109	4109	4109	4109	4109
Maple	Min	0	-25	0	0.23	0	0.0629	2	9.37
	Max	5	6	61.33	24.1	7.29	1	46	13
	Average	0.06	-3.61	19.94	13.42	0.18	0.7362	20.74	11.9
	St.Dev	0.27	4.48	10.88	6.5	0.31	0.2302	11.94	0.5
	N	4532	4532	4532	4532	4532	4532	4532	4532
Patrol 3	Min	0	-22.5	0	0.35	0	0.0715	2	9.96
	Max	3	11	68.5	19.55	6.8	1	47	14.25
	Average	0.09	-3.72	22.8	12.13	0.21	0.7436	19.24	12.02
	St.Dev	0.32	4.57	11.77	6.66	0.33	0.206	12.54	0.74
	N	3635	3635	3635	3635	3635	3635	3635	3635
Patrol 2	Min	0	-26	0.33	0.1	0	0.0758	2	9.71
	Max	6	12.95	58	24.1	6.12	1	46	13.39
	Average	0.14	-3.96	18.3	12.7	0.2	0.7663	17.57	11.54
	St.Dev	0.45	4.58	10.33	7.61	0.31	0.2151	11.64	0.72
	N	4117	4117	4117	4117	4117	4117	4117	4117

Appendix L: Accident Seasonal Trend Plots

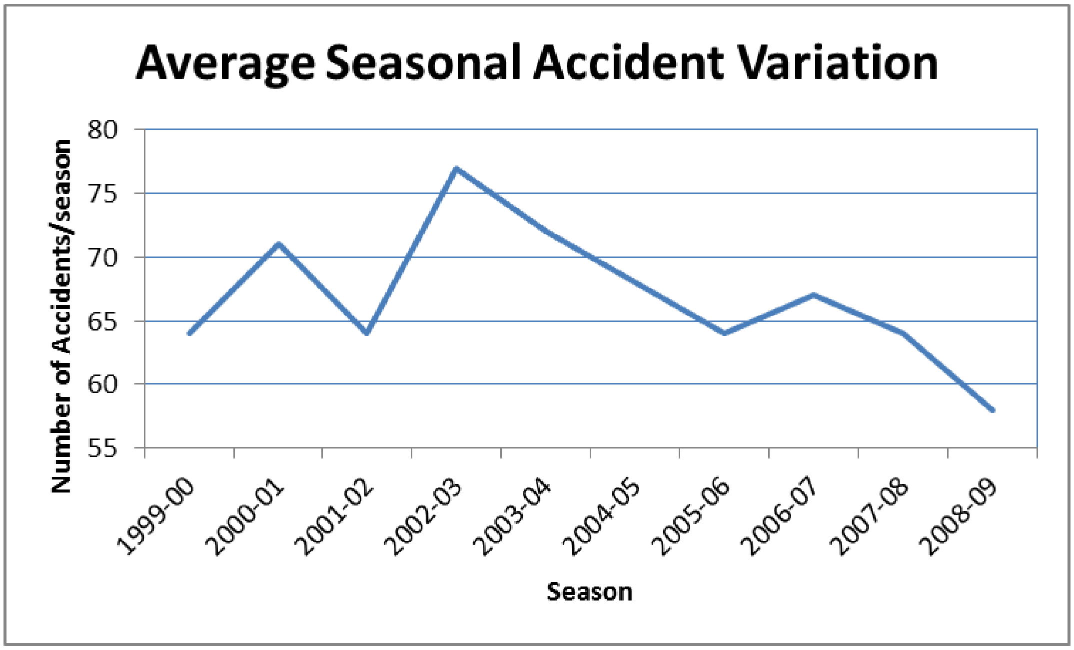


Figure L – 1: Seasonal variation of accidents for all sites combined

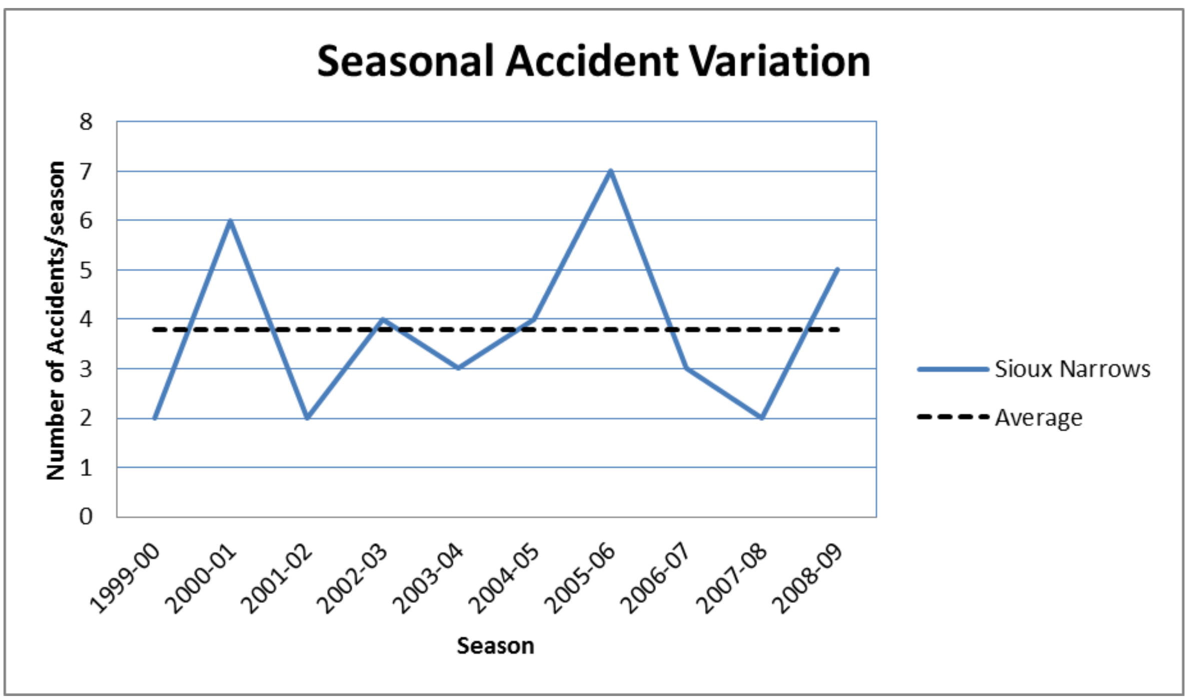


Figure L – 2: Seasonal variation of accidents – Sioux Narrows

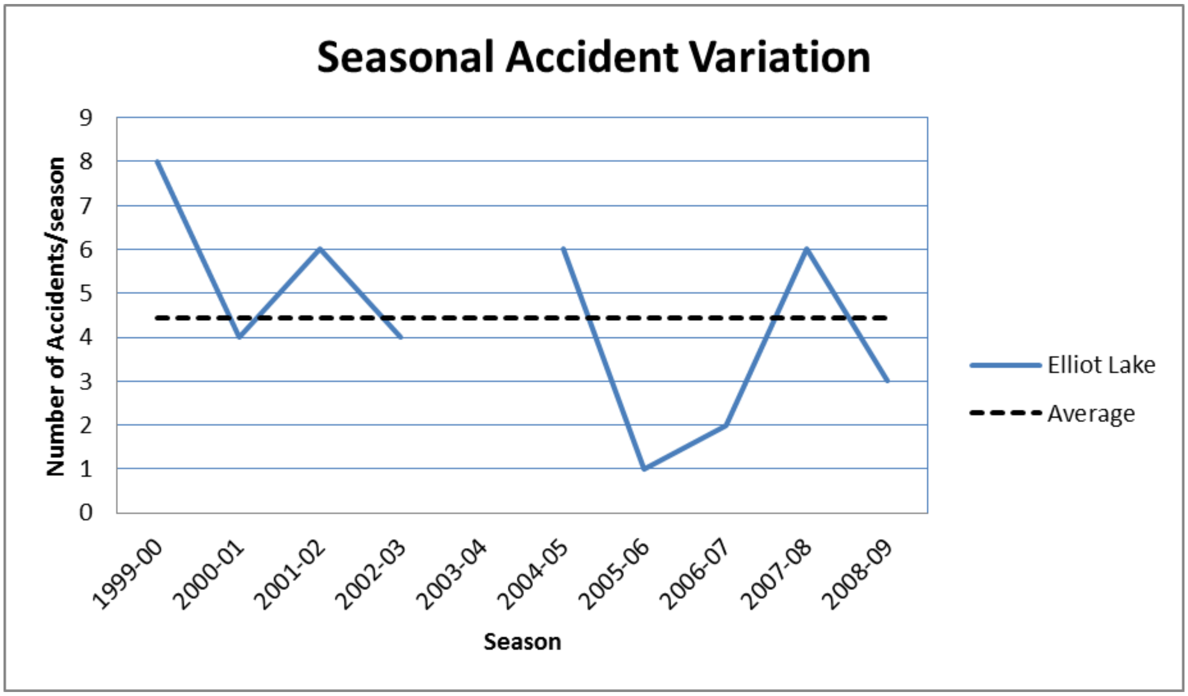


Figure L – 3: Seasonal variation of accidents – Elliot Lake

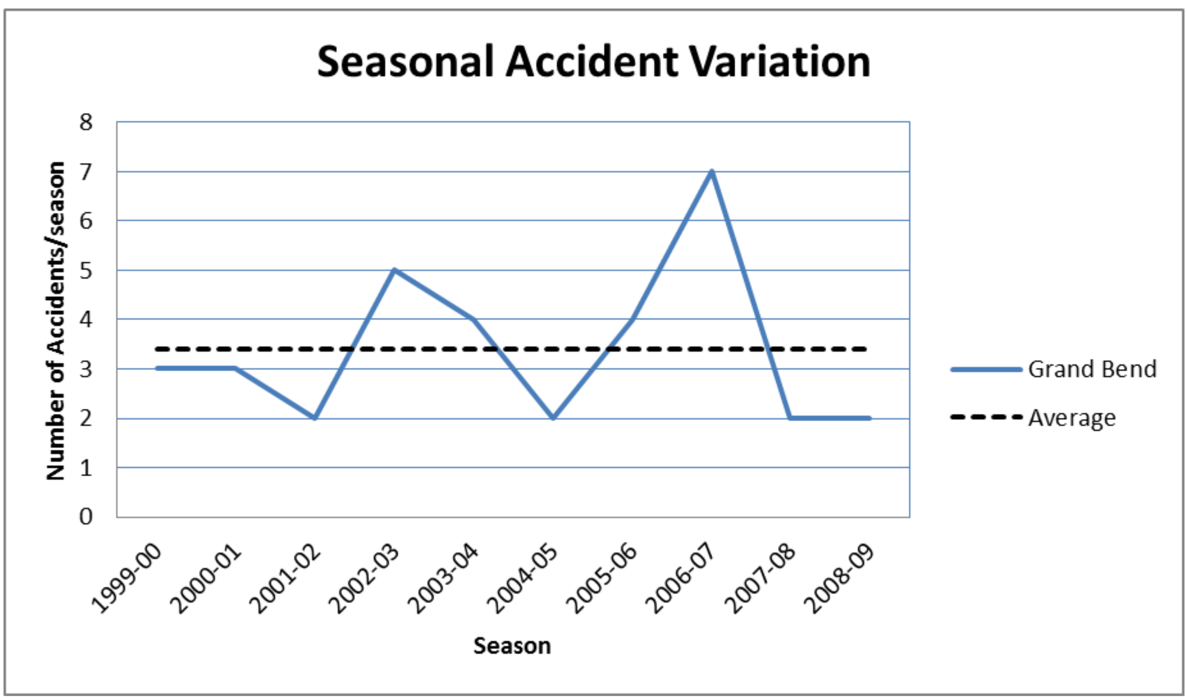


Figure L – 4: Seasonal variation of accidents – Grand Bend

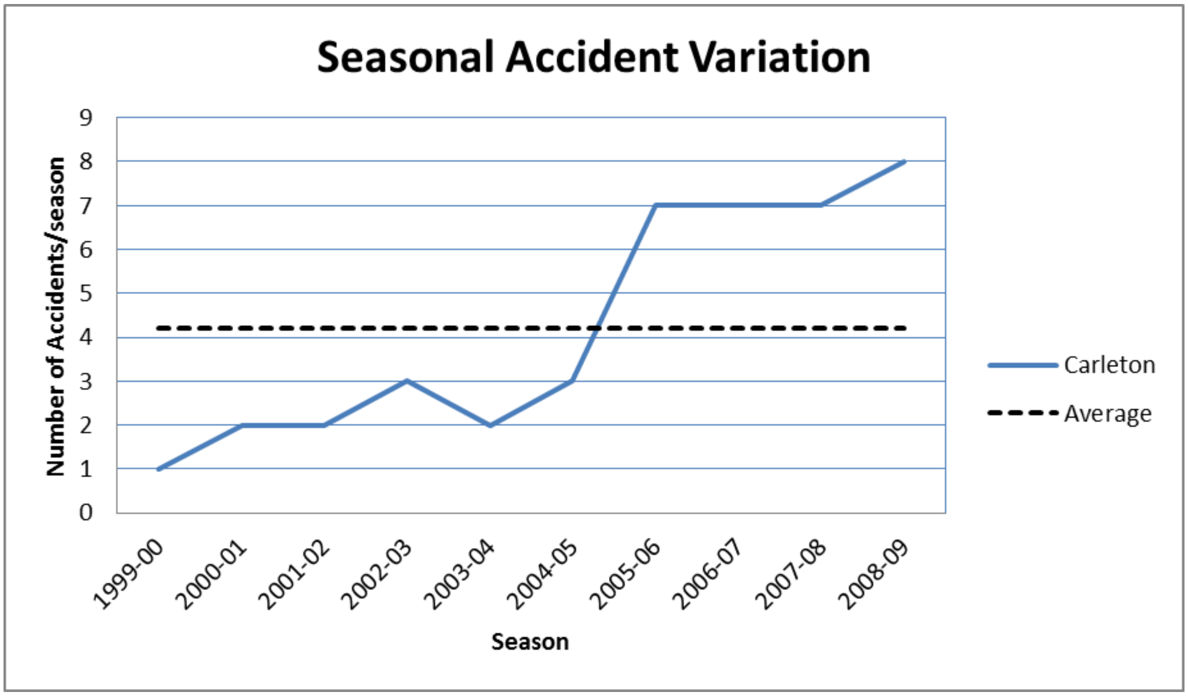


Figure L – 5: Seasonal variation of accidents – Carleton

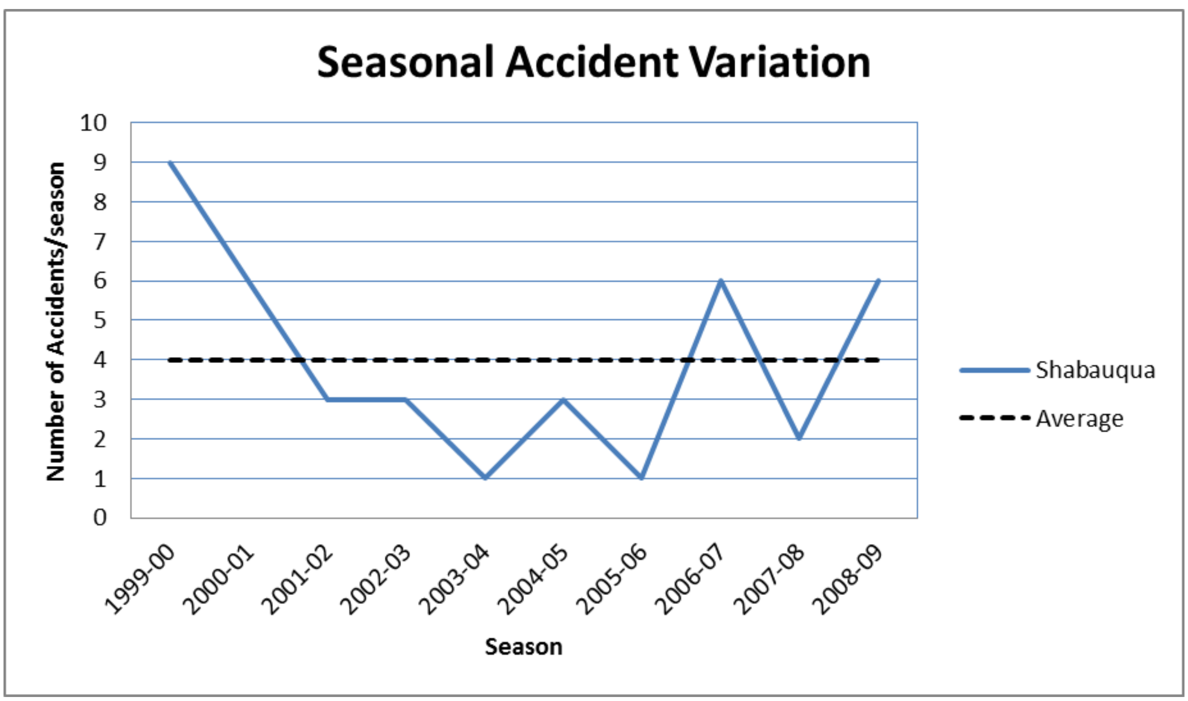


Figure L – 6: Seasonal variation of accidents – Shabauqua

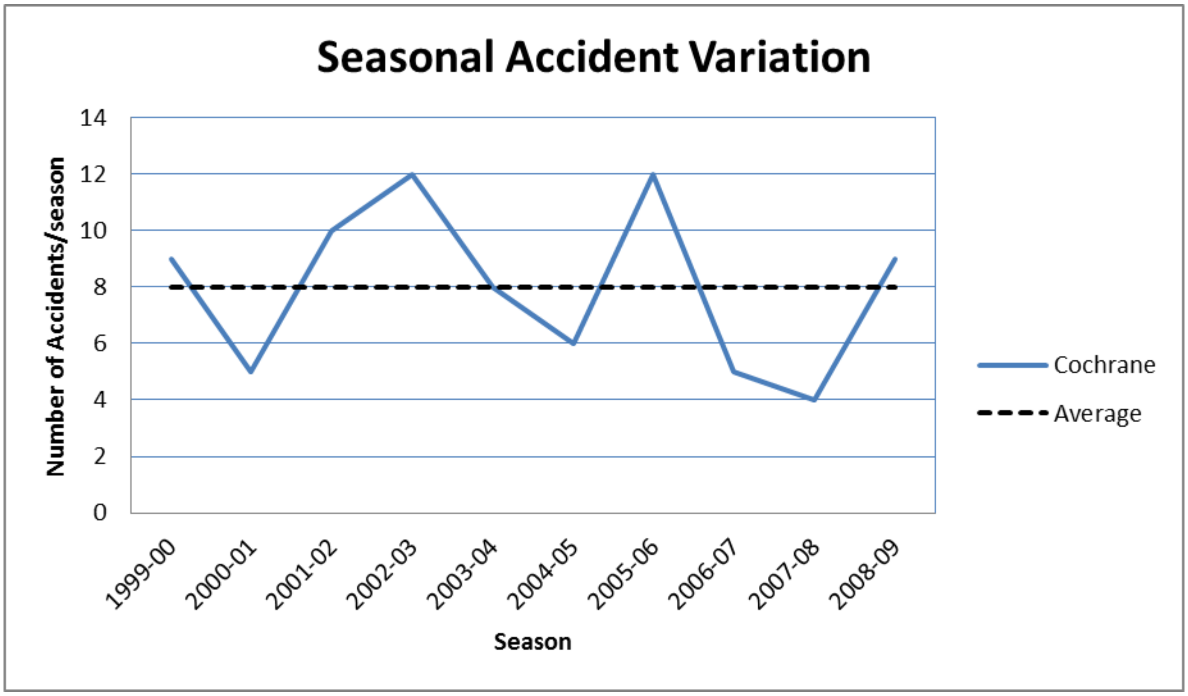


Figure L – 7: Seasonal variation of accidents – Cochrane

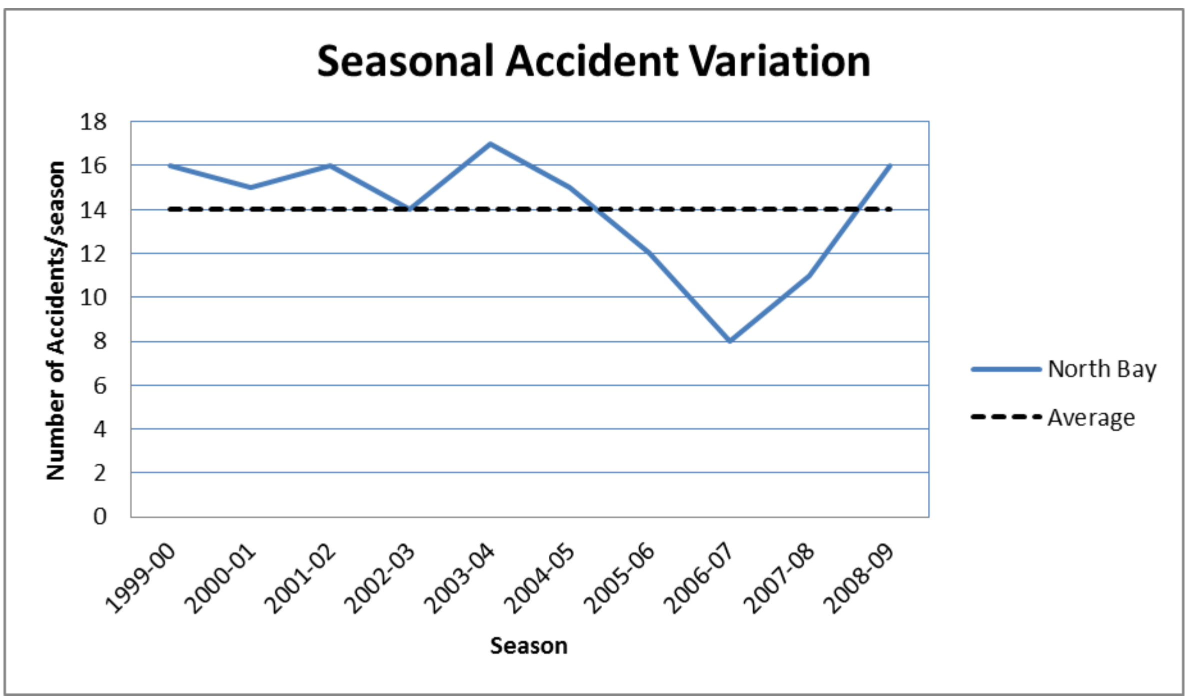


Figure L – 8: Seasonal variation of accidents – North Bay

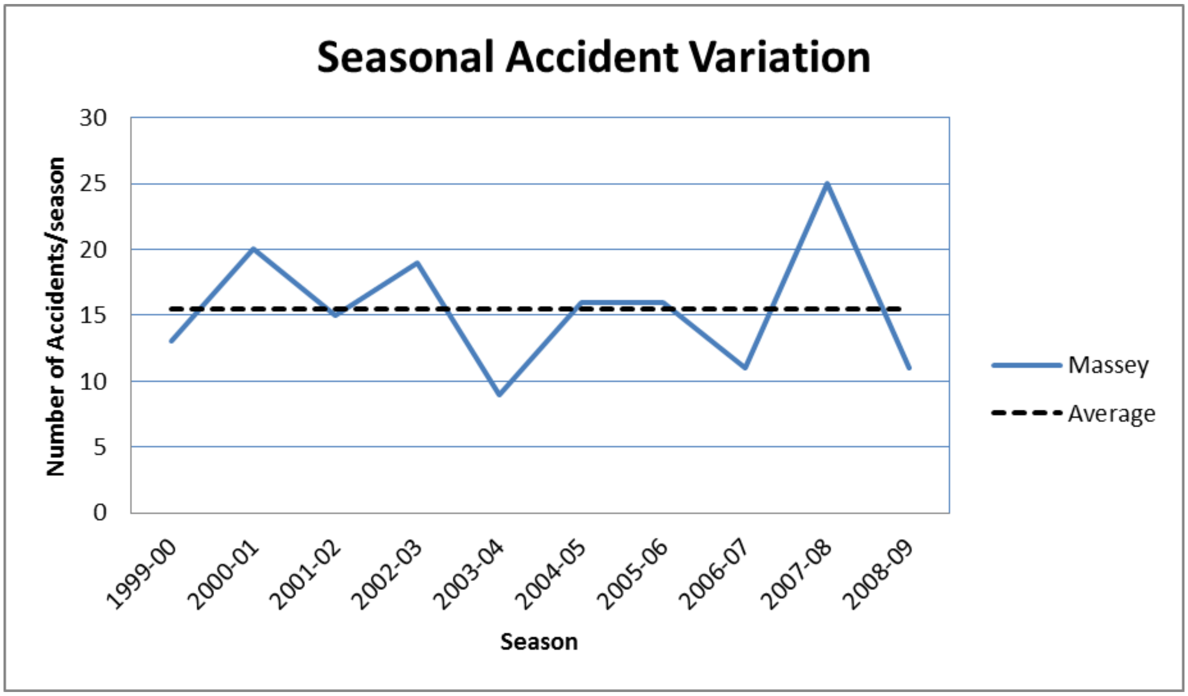


Figure L – 9: Seasonal variation of accidents – Massey

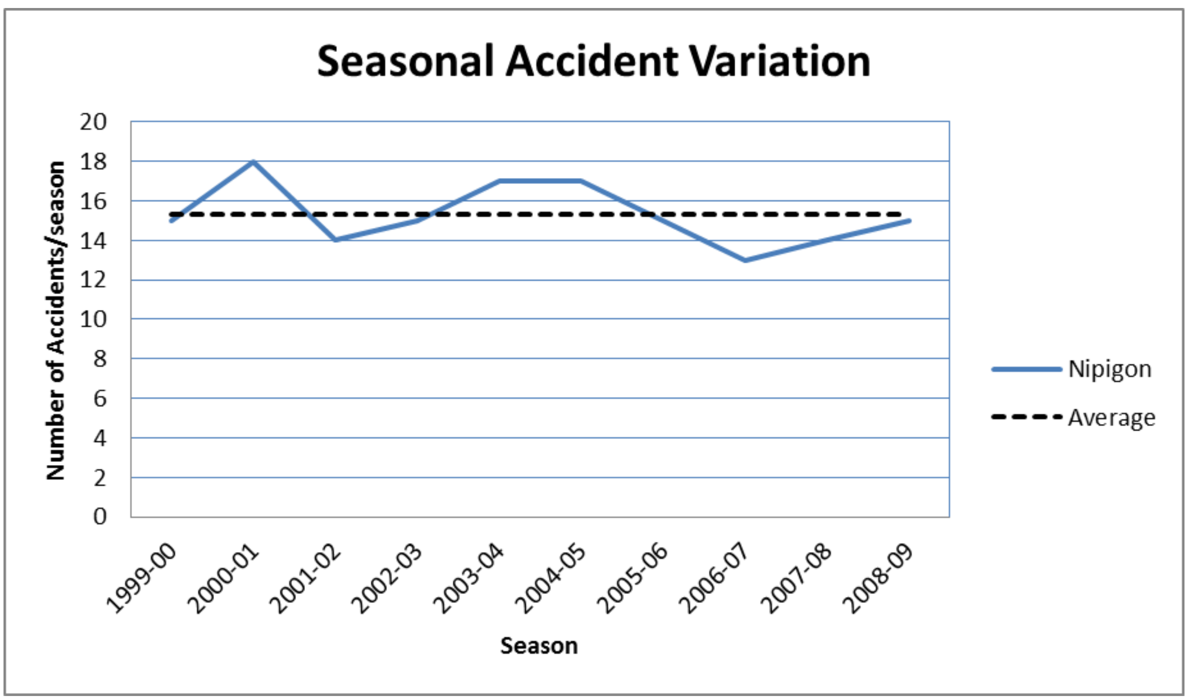


Figure L – 10: Seasonal variation of accidents – Nipigon

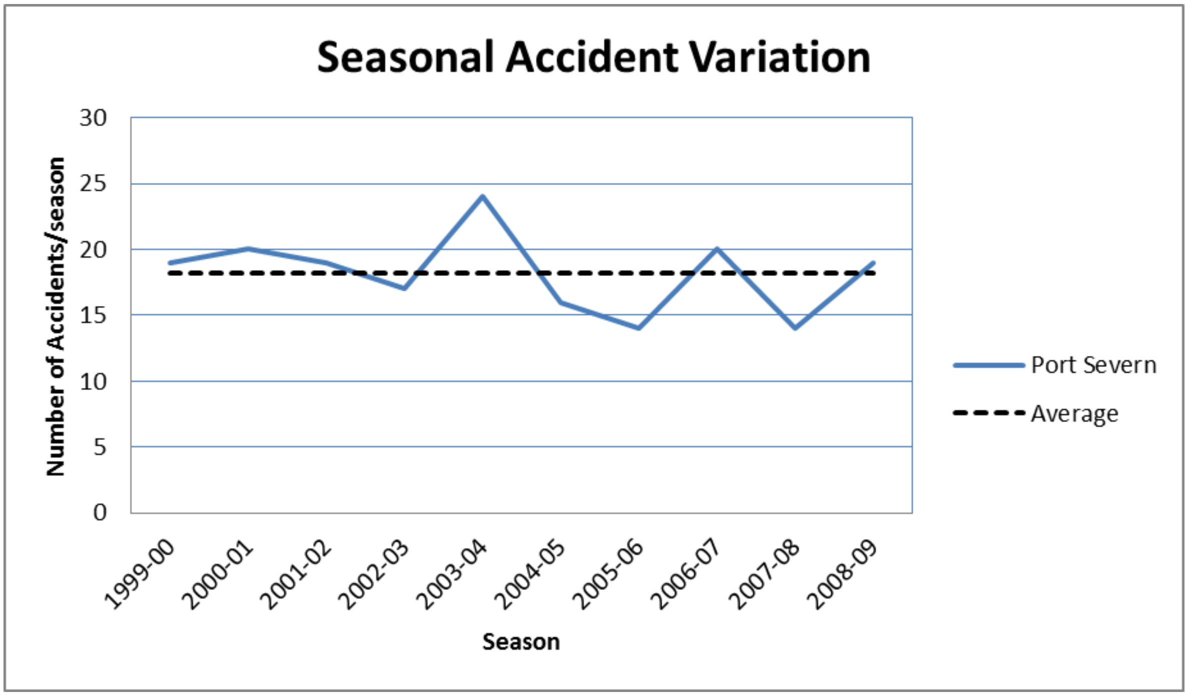


Figure L – 11: Seasonal variation of accidents – Port Severn

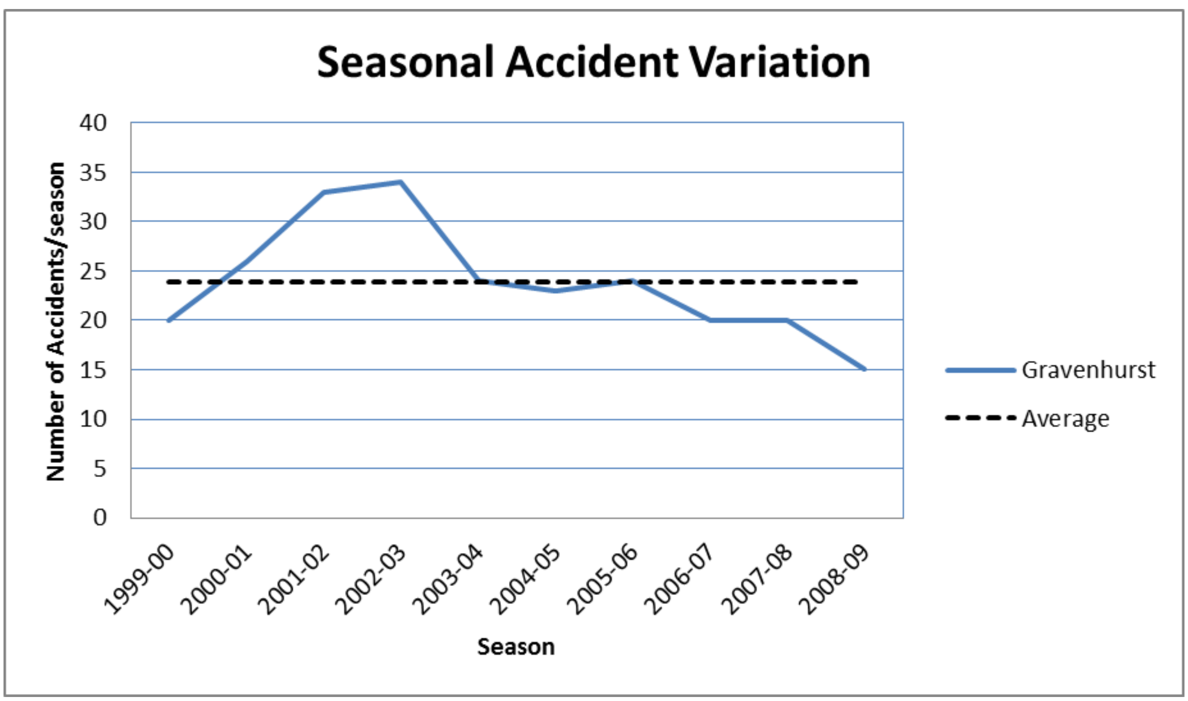


Figure L – 12: Seasonal variation of accidents – Gravenhurst

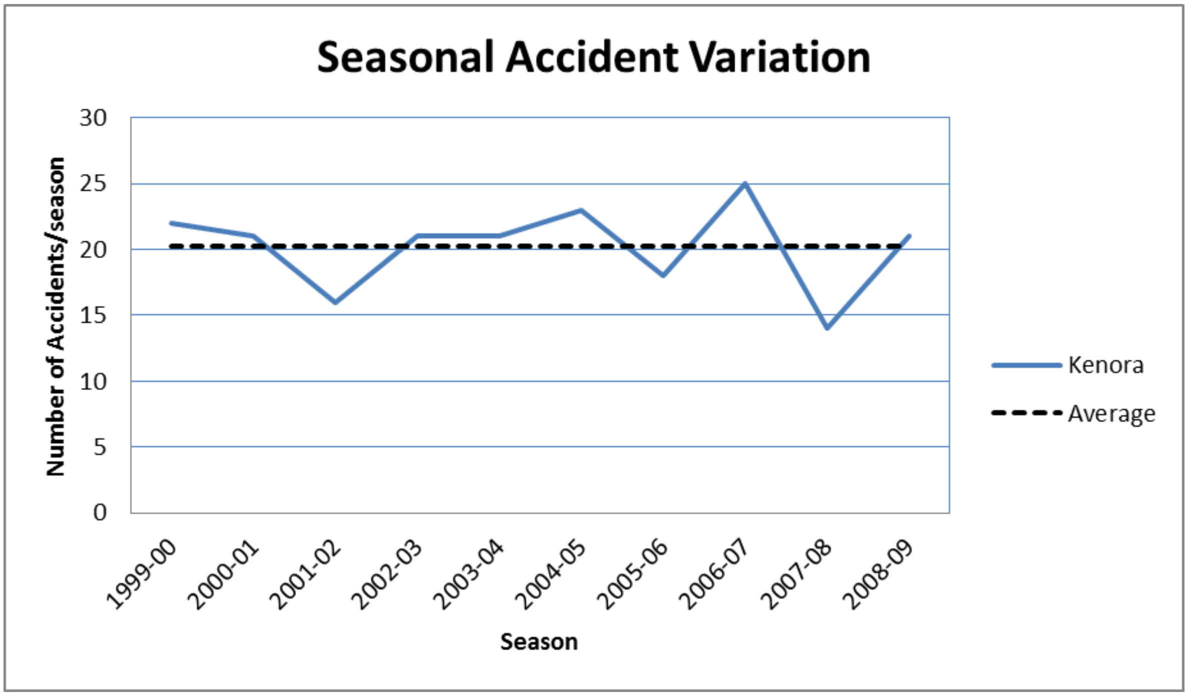


Figure L – 13: Seasonal variation of accidents – Kenora

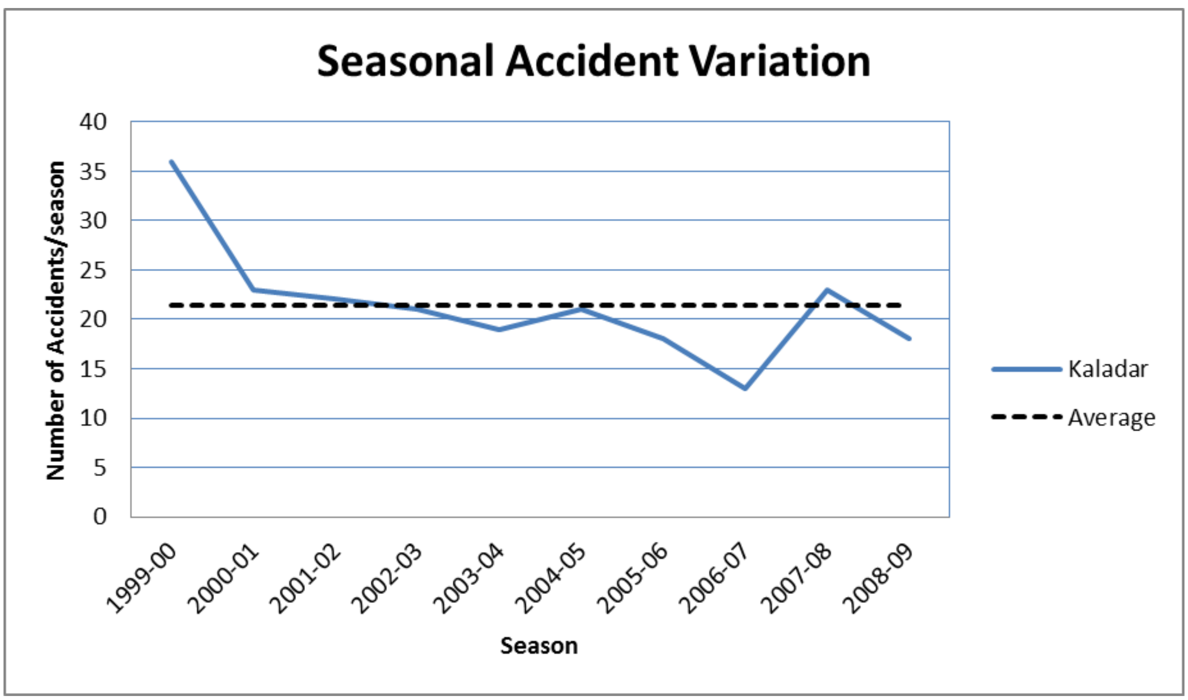


Figure L – 14: Seasonal variation of accidents – Kaladar

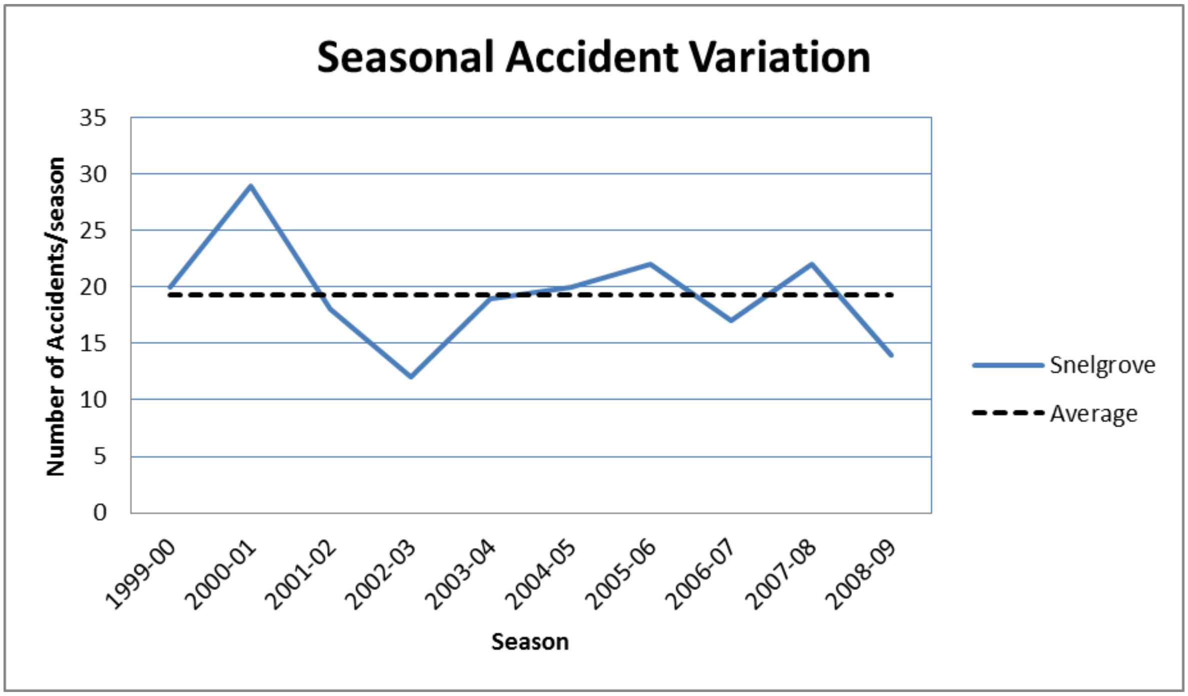


Figure L – 15: Seasonal variation of accidents – Snelgrove

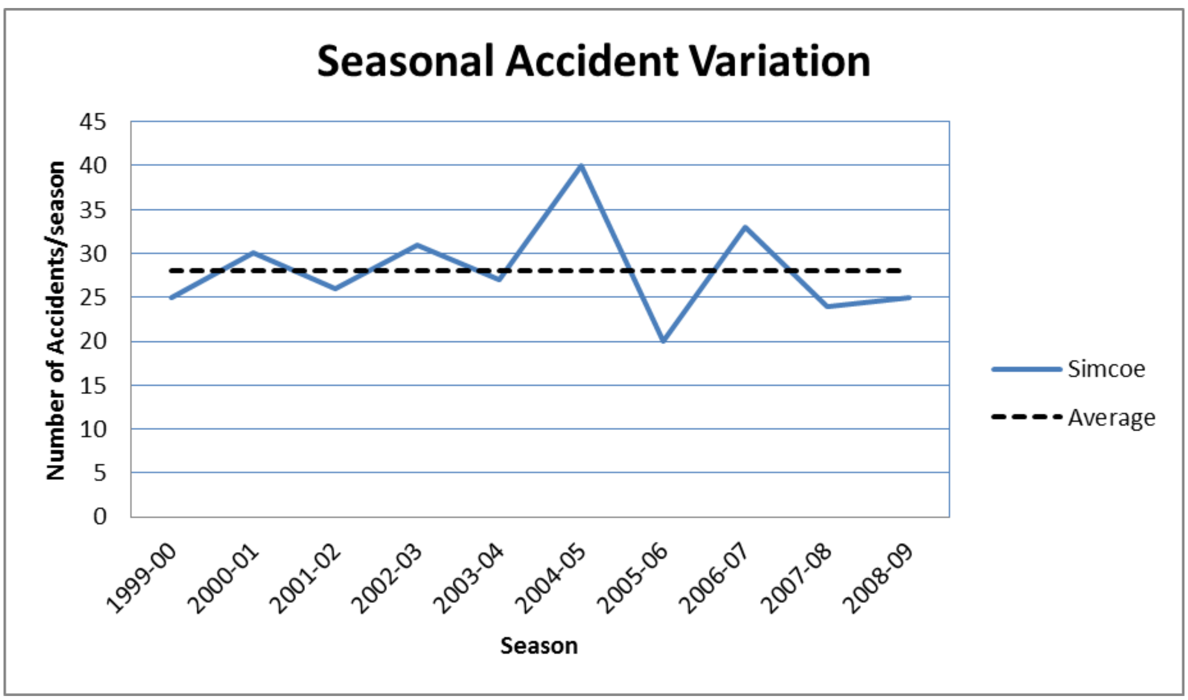


Figure L – 16: Seasonal variation of accidents – Simcoe

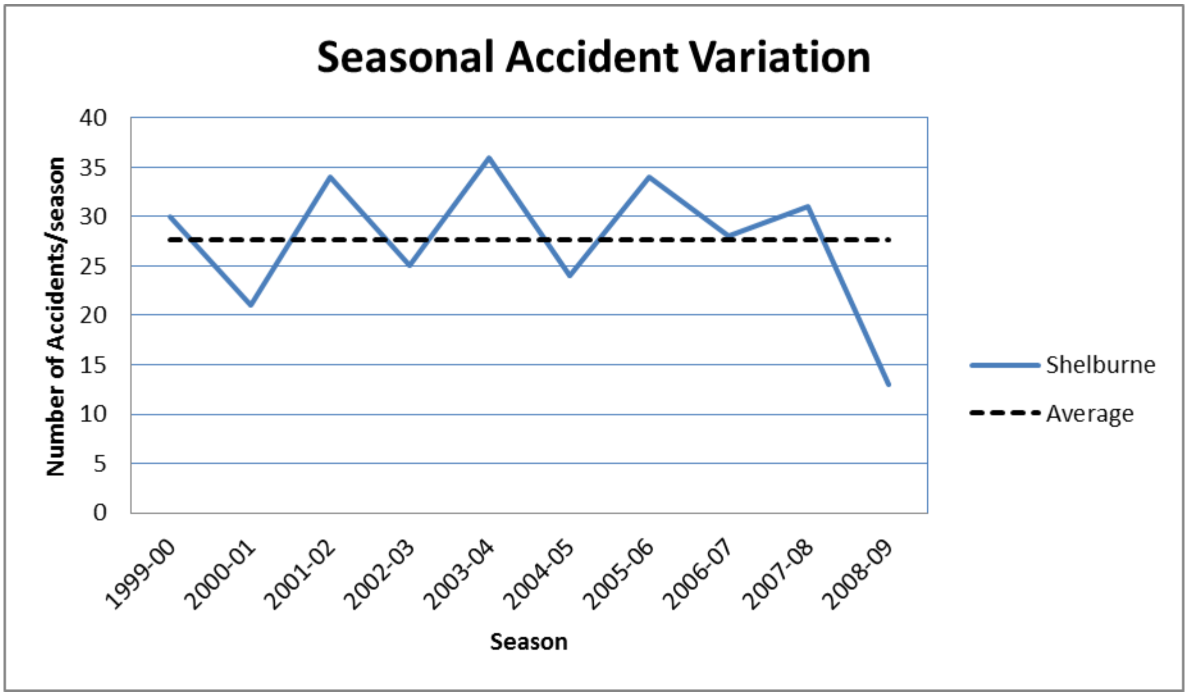


Figure L – 17: Seasonal variation of accidents – Shelburne

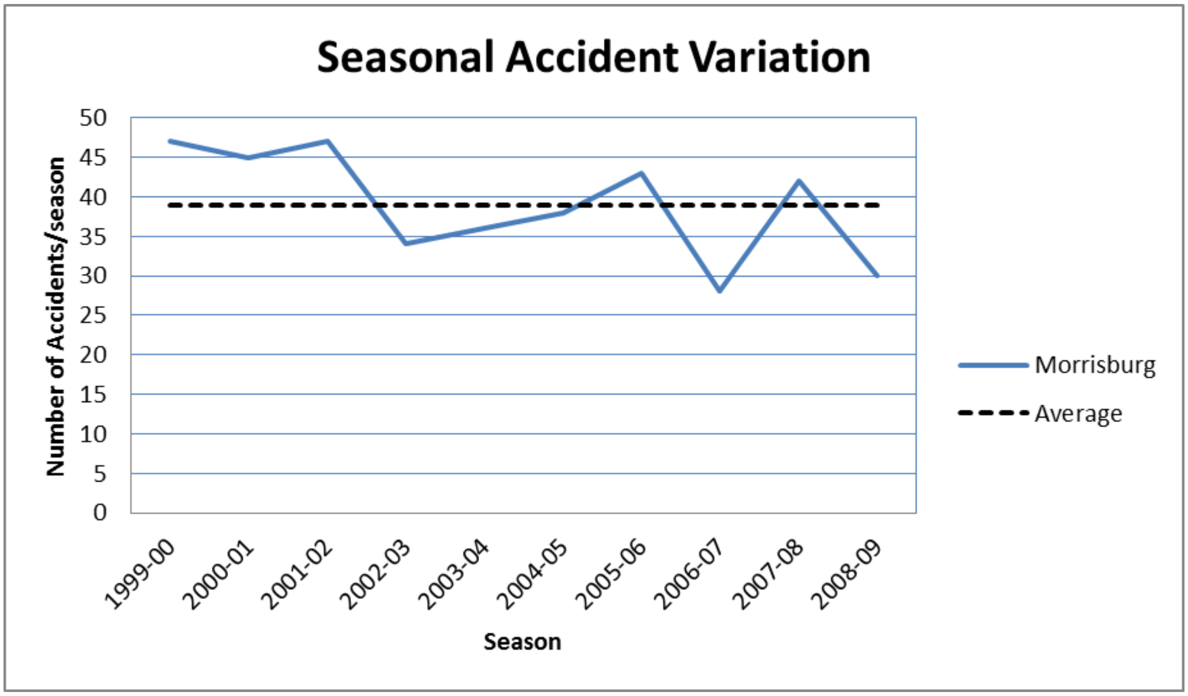


Figure L – 18: Seasonal variation of accidents – Morrisburg

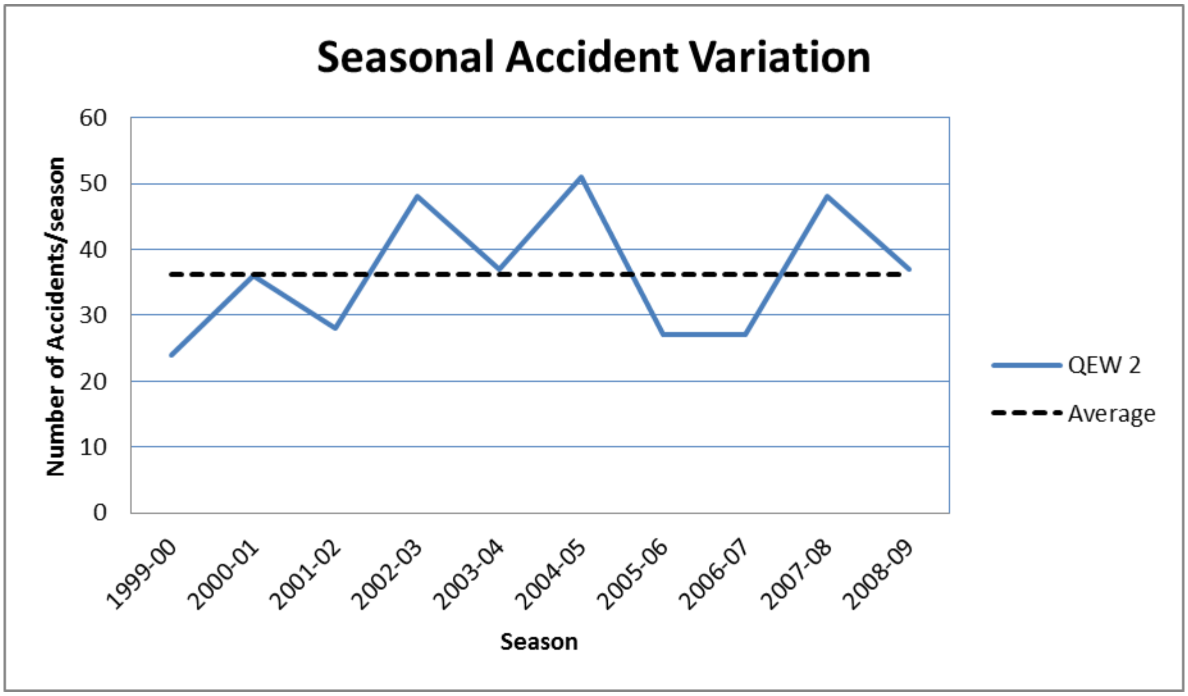


Figure L – 19: Seasonal variation of accidents – QEW 2

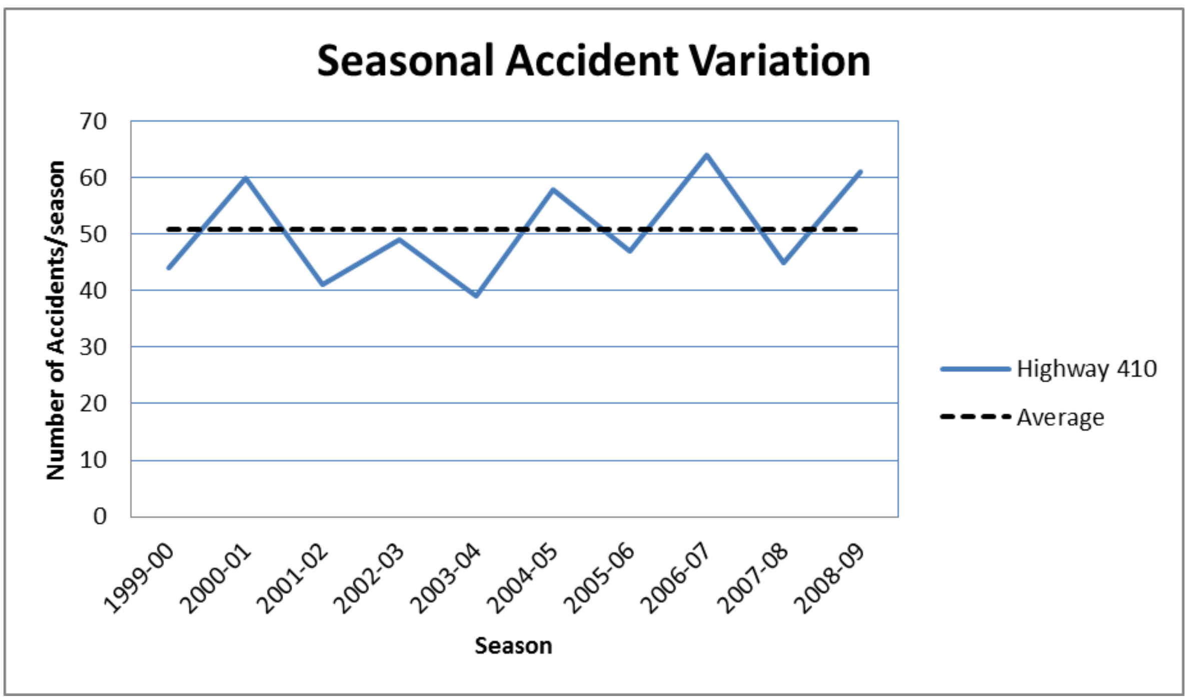


Figure L – 20: Seasonal variation of accidents – Highway 410

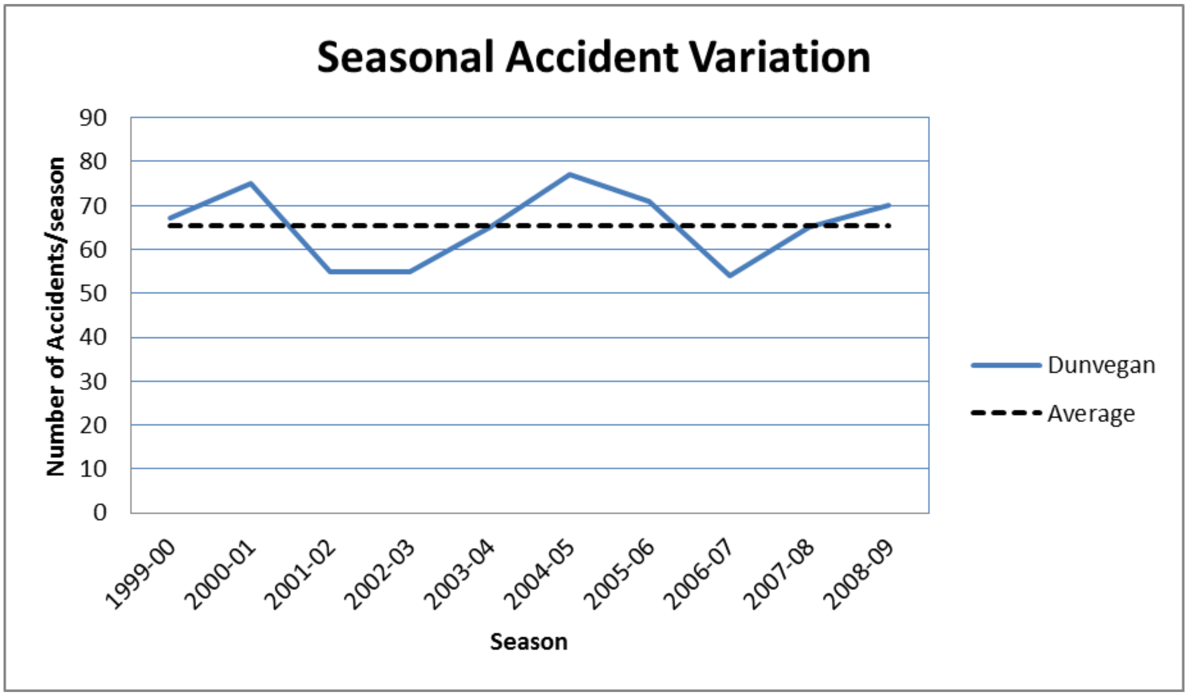


Figure L – 21: Seasonal variation of accidents – Dunvegan

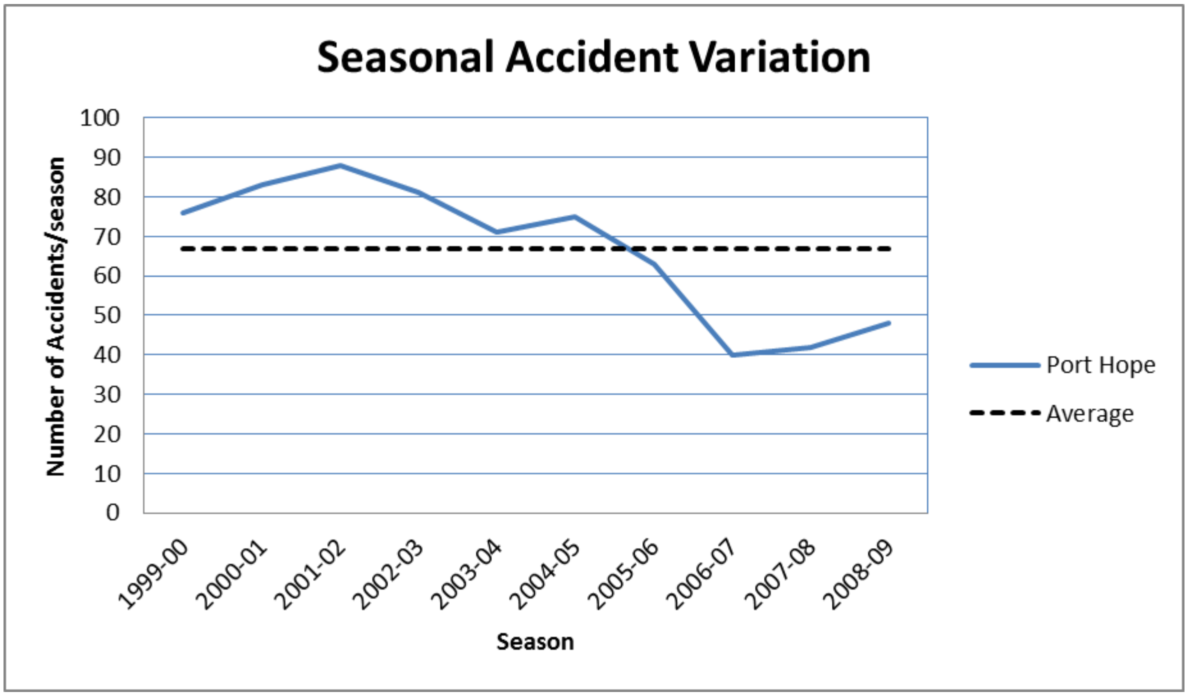


Figure L – 22: Seasonal variation of accidents – Port Hope

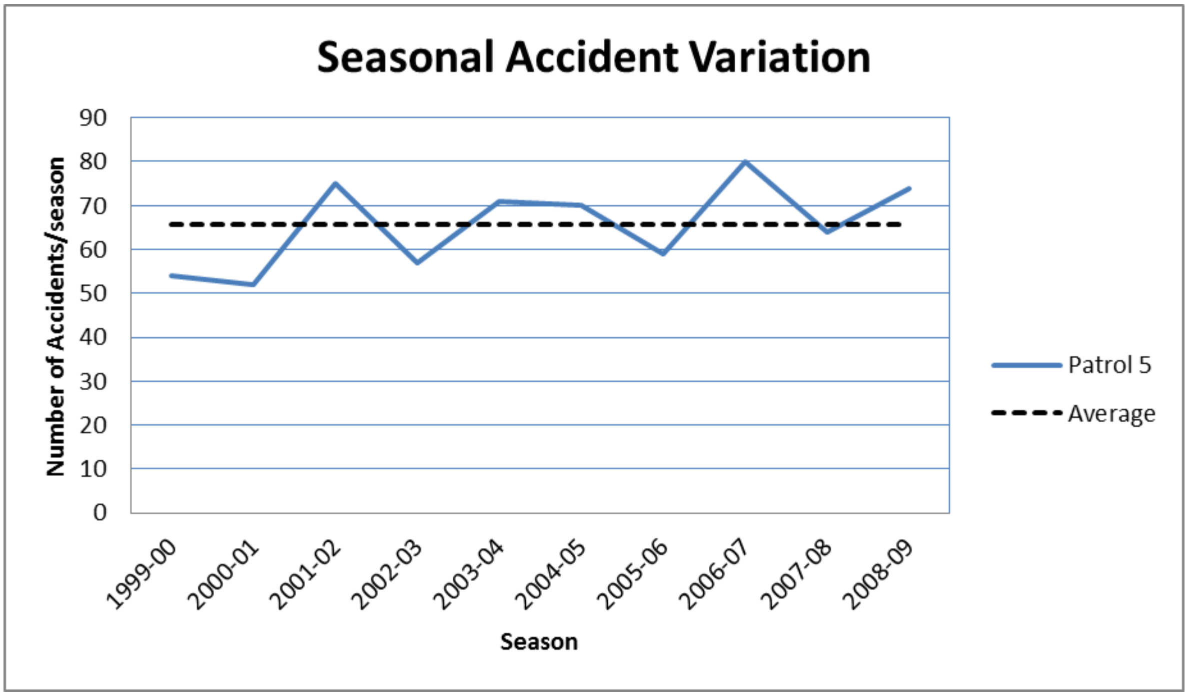


Figure L – 23: Seasonal variation of accidents – Patrol 5

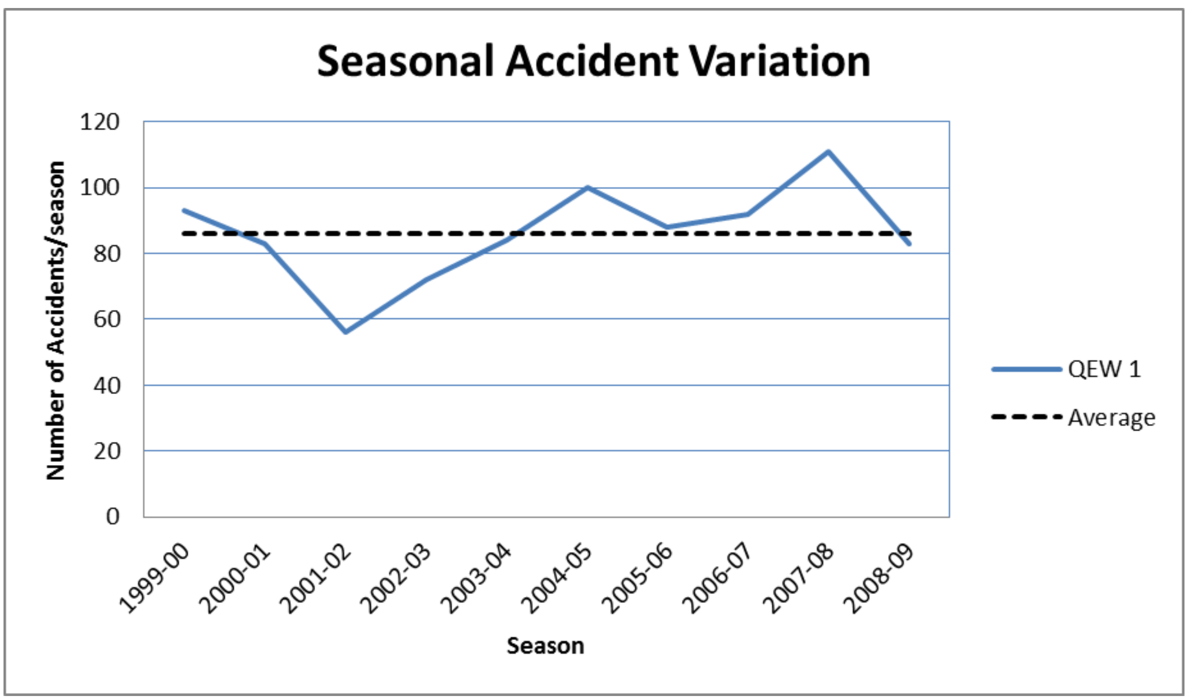


Figure L – 24: Seasonal variation of accidents – QEW 1

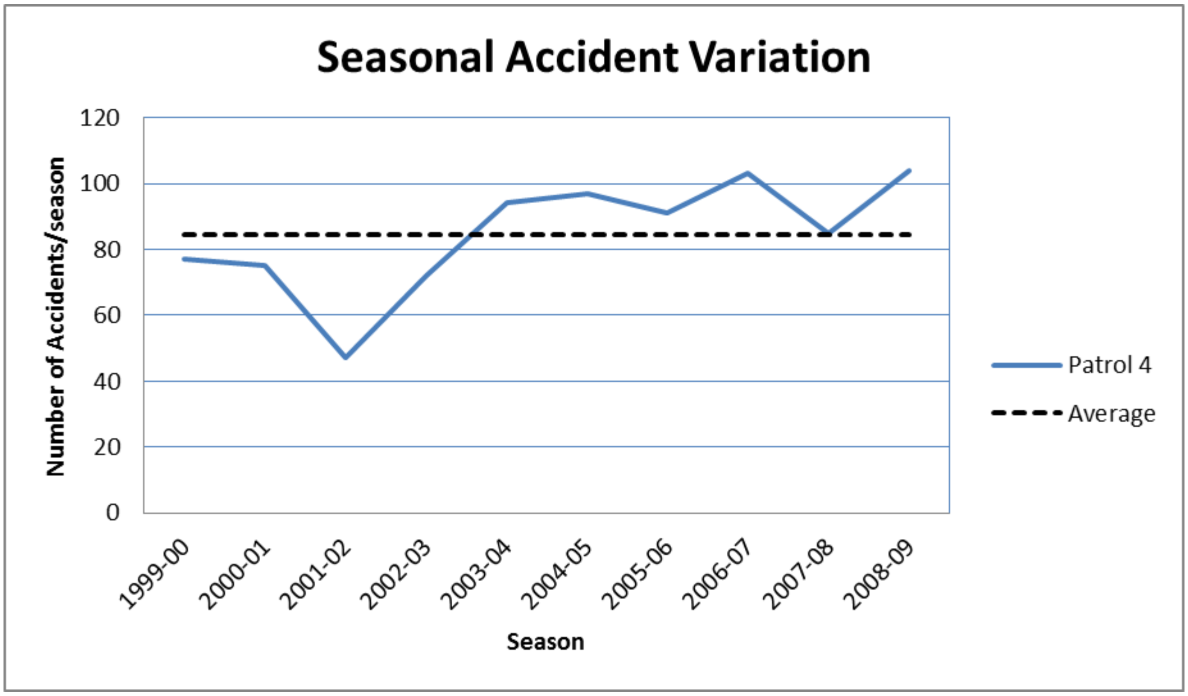


Figure L – 25: Seasonal variation of accidents – Patrol 4

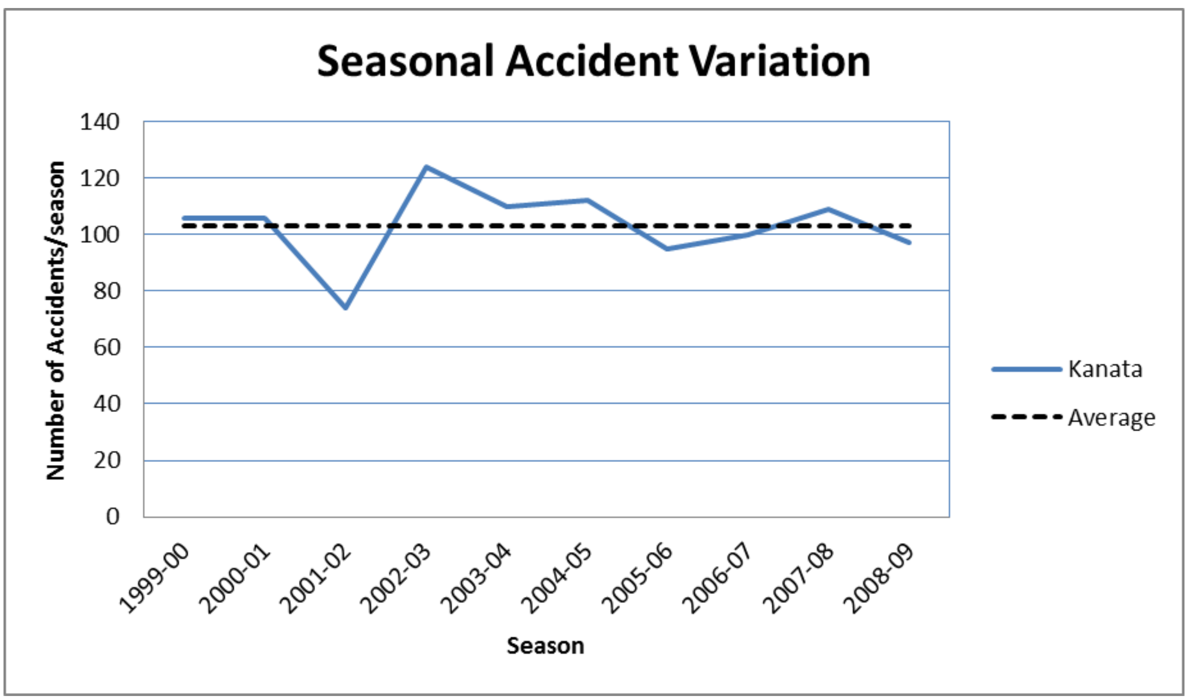


Figure L – 26: Seasonal variation of accidents – Kanata

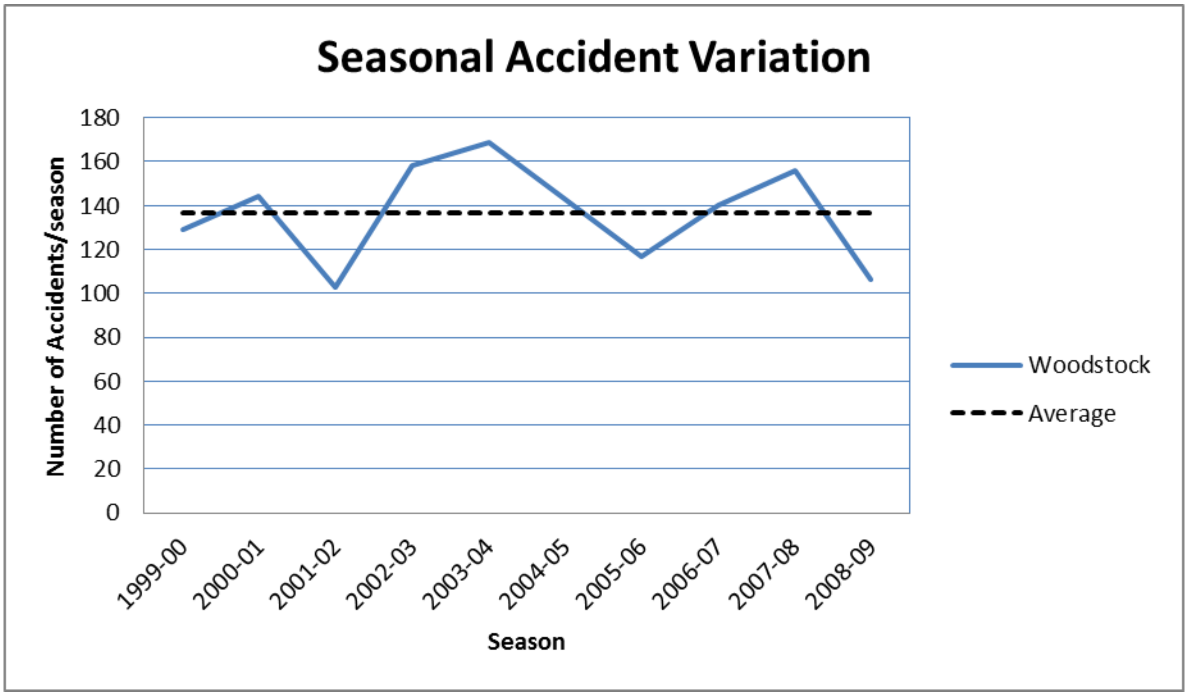


Figure L – 27: Seasonal variation of accidents – Woodstock

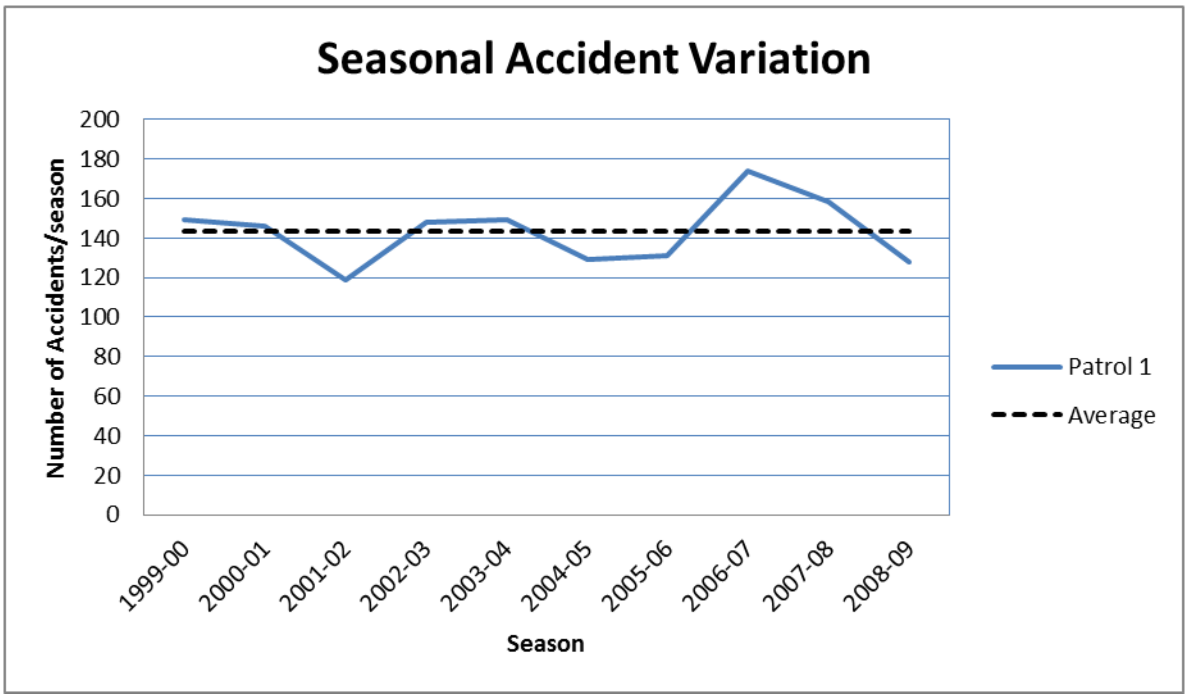


Figure L – 28: Seasonal variation of accidents – Patrol 1

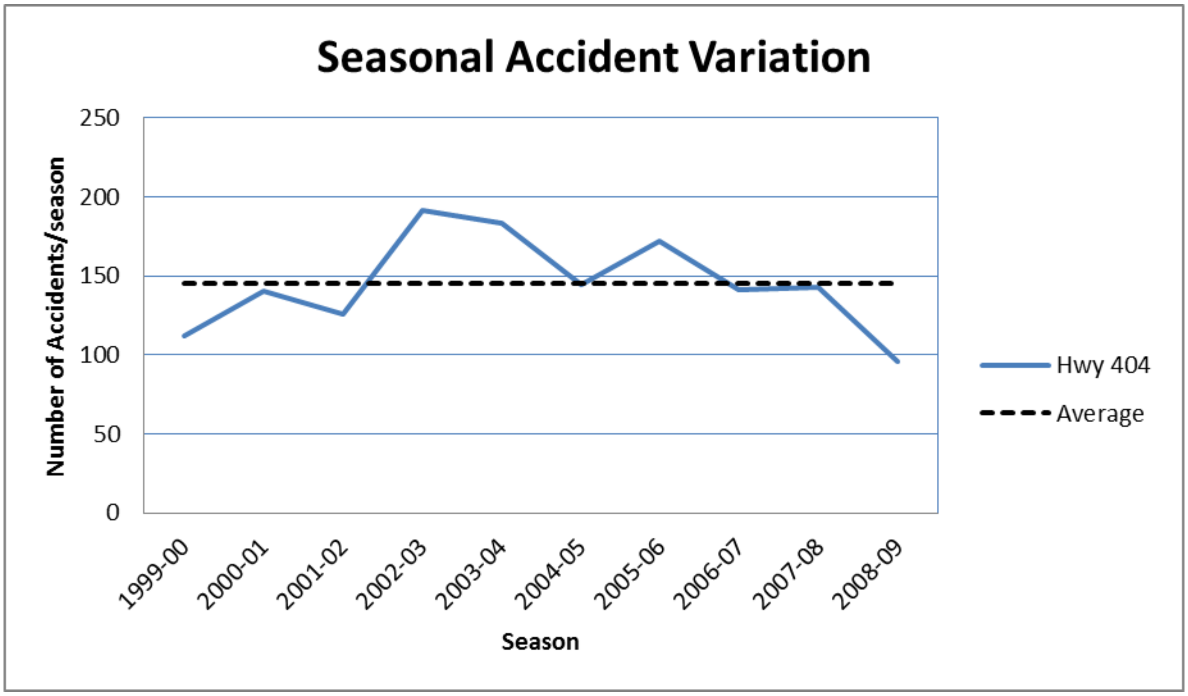


Figure L – 29: Seasonal variation of accidents – Highway 404

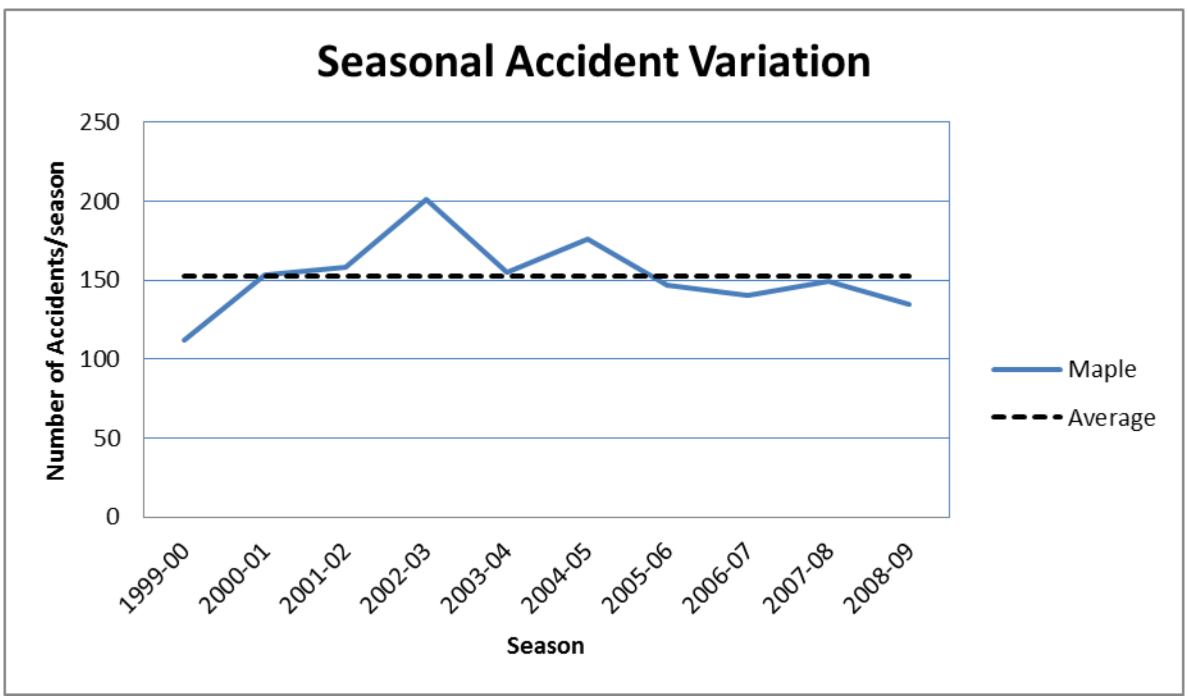


Figure L – 30: Seasonal variation of accidents – Maple

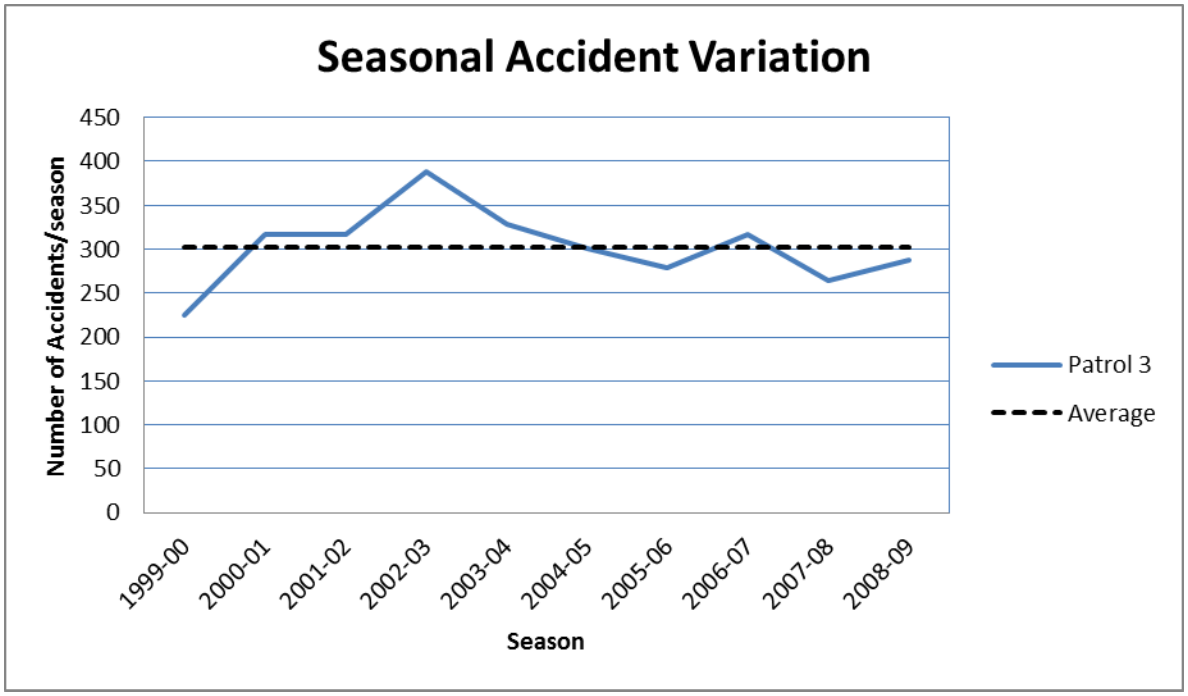


Figure L – 31: Seasonal variation of accidents – Patrol 3

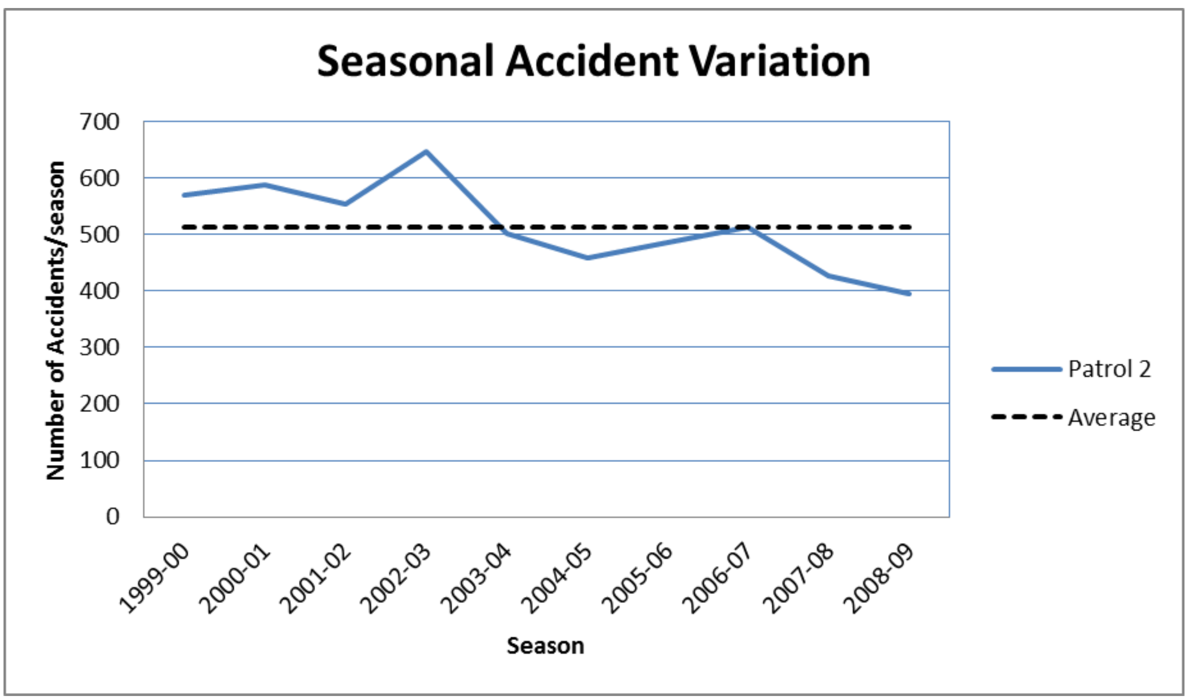


Figure L – 32: Seasonal variation of accidents – Patrol 2

Appendix M: EBD – Individual Sites Results Using GNB and Combined EBD Using NB

TABLE M – 1: EBD Results for Individual Sites

	Wood Stock		**Snelgrove**		**Sioux Narrows**		**Simcoe**		**Shelburne**		**Shabauqua**		**QEW2**	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-2.859	0.066	-6.486	0.174	0.764	0.698	-13.134	0.000	-5.867	0.086	-24.376	0.181	-7.663	0.012
Monthly ID														
Air Temperature									0.165	0.008			-0.061	0.064
Wind Speed					0.102	0.069								
visibility (km)													-0.070	0.090
Precipitation	0.034	0.009											0.046	0.022
RSI	-4.146	0.000	-4.834	0.008	-9.273	0.004	-4.248	0.000	-6.452	0.000	-14.065	0.069	-0.875	0.535
Ln(Exposure)	0.395	0.001	0.587	0.063			1.131	0.000	0.770	0.001	2.639	0.086	0.566	0.015
Sanding done														
Sanding not done														
Salting done														
Salting not done														
Anti Icing done									-1.115	0.070				
Anti Icing not done									0.000					
BPR time							-0.132	0.023					-0.101	0.194
Ln(Alpha)			-1.309		0.617						-33.305			
Constant	3.023	0.430					-3.352	0.902	10.739	0.369			-23.627	0.069
BPR time														
RSI	9.030	0.006					8.762	0.509	-3.473	0.513			40.937	0.000
Ln(Exposure)	-0.690	0.011					-0.296	0.863	-0.638	0.445			-0.687	0.392
Observations	409		370		348		385		403		203		321	
LL(Null)	-382.51		-93.15		-28.94		-146.68		-133.75		-19.71		-154.75	
LL(Model)	-348.44		-79.23		-24.20		-130.58		-113.96		-11.42		-137.10	
AIC	710.87		166.45		56.41		275.16		243.92		28.85		294.21	

TABLE M – 2: EBD Results for Individual Sites

	QEW1		Port Severn		Port Hope		Patrol 5		Patrol 4		Patrol 3		Patrol 2	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-4.236	0.072	-5.749	0.095	-10.620	0.000	-8.304	0.016	-10.864	0.000	-2.951	0.034	-4.414	0.000
Monthly ID														
Air Temperature (C^o)							-0.083	0.034					-0.028	0.110
Wind Speed (Km/hr)			0.106	0.005	0.031	0.013								
visibility (km)					-0.041	0.078	-0.073	0.119						
Precipitation											0.095	0.000	0.073	0.000
RSI	-9.525	0.000	-3.499	0.058	-6.765	0.000	-4.318	0.012	-2.913	0.001	-4.755	0.000	-4.148	0.000
Ln(Exposure)	0.790	0.000	0.406	0.075	1.105	0.000	0.797	0.000	0.819	0.000	0.409	0.000	0.537	0.000
Sanding done														
Sanding not done														
Salting done														
Salting not done														
Anti Icing done									1.291	0.025				
Anti Icing not done									0.000					
BPR time	-0.107	0.080									-0.046	0.044	-0.053	0.032
Ln(Alpha)														
Constant	1.418	0.796	-18.400	0.327	-9.126	0.081	22.100	0.016	20.166	0.092	-7.066	0.423	6.041	0.043
BPR time														
RSI	-3.134	0.291	16.694	0.263	1.122	0.595	-5.218	0.423	79.912	0.000	-3.547	0.110	-1.146	0.403
Ln(Exposure)	0.055	0.888	0.498	0.606	0.594	0.111	-1.386	0.057	-7.134	0.000	0.556	0.302	-0.393	0.056
Observations	360		432		295		315		285		351		438	
LL(Null)	-204.84		-106.44		-264.59		-131.49		-144.58		-412.87		-623.71	
LL(Model)	-180.45		-94.55		-245.49		-111.32		-127.51		-341.95		-532.75	
AIC	374.89		203.11		506.97		238.65		269.02		699.91		1083.51	

TABLE M – 3: EBD Results for Individual Sites

	Patrol 1		North Bay		Nipigon		Morrisburg		Massey		Maple		Kenora	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-0.945	0.659	-11.352	0.011	-16.027	0.012	-2.859	0.246	-7.781	0.018	-11.087	0.000	-6.732	0.109
Monthly ID													-0.318	0.003
Air Temperature (C^{o})														
Wind Speed (Km/hr)	-0.033	0.057									0.023	0.009		
visibility (km)											-0.081	0.000	-0.094	0.049
Precipitation	0.050	0.004												
RSI	-6.976	0.000			1.831	0.526	-5.979	0.000			-3.461	0.000	-1.683	0.261
Ln(Exposure)	0.401	0.001	0.808	0.037	1.098	0.015	0.443	0.009	0.530	0.056	0.920	0.000	0.689	0.016
Sanding done														
Sanding not done														
Salting done														
Salting not done														
Anti Icing done											0.443	0.130		
Anti Icing not done											0.000			
BPR time														
Ln(Alpha)														
Constant	2.489	0.570	168.684	0.000	-9.695	0.741	-2.329	0.619	-47.883	0.079	5.655	0.440	31.535	0.052
BPR time														
RSI	2.070	0.390			26.512	0.161	1.971	0.768	62.894	0.065	4.866	0.042	-6.440	0.245
Ln(Exposure)	-0.258	0.343	-15.803	0.000	-0.706	0.626					-0.648	0.159	-2.270	0.065
Observations	424		424		217		329		261		382		409	
LL(Null)	-312.62		-92.14		-56.34		-164.65		-80.86		-374.91		-125.02	
LL(Model)	-266.58		-90.04		-54.27		-145.36		-78.73		-319.26		-111.88	
AIC	549.16		188.08		120.53		300.72		165.46		656.51		239.77	

TABLE M – 4: EBD Results for Individual Sites

	Kanata		**Kaladar**		**Graven Hurst**		**Grand Bend**		**Elliot Lake**	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-3.938	0.112	-4.678	0.179	-4.091	0.160	-0.978	0.874	-19.175	0.043
Monthly ID					-0.396	0.001	-0.617	0.120		
Air Temperature (C^o)					0.073	0.054	-0.231	0.048		
Wind Speed (Km/hr)							-0.119	0.071	0.196	0.099
visibility (km)							-0.336	0.011		
Precipitation										
RSI	-5.599	0.000	-5.132	0.001	-3.309	0.011	-6.205	0.047		
Ln(Exposure)	0.501	0.001	0.520	0.053	0.495	0.016	0.740	0.184	1.313	0.166
Sanding done										
Sanding not done										
Salting done										
Salting not done										
Anti Icing done										
Anti Icing not done										
BPR time					0.060	0.044				
Ln(Alpha)			-34.496		-0.592		-65.851		2.454	
Constant	20.381	0.039								
BPR time										
RSI	-6.532	0.226								
Ln(Exposure)	-1.172	0.034								
Observations	369		334		388		265		276	
LL(Null)	-238.79		-89.81		-165.14		-28.73		-23.48	
LL(Model)	-211.70		-79.62		-143.60		-19.84		-19.52	
AIC	435.41		165.25		301.20		53.68		47.04	

TABLE M – 5: EBD Results for Individual Sites

	Dunvegan		Cochrane		Carleton		410		404	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-7.326	0.001	-10.968	0.053	-36.617	0.074	-7.664	0.031	-15.079	0.000
Monthly ID					-1.290	0.078				
Air Temperature (C^o)									-0.049	0.010
Wind Speed (Km/hr)	-0.052	0.010	0.076	0.018						
visibility (km)	-0.040	0.111					-0.068	0.061	-0.036	0.045
Precipitation							0.067	0.001		
RSI	-3.036	0.003	-6.619	0.003	-10.998	0.143	-4.673	0.000	-3.264	0.000
Ln(Exposure)	0.695	0.000	1.009	0.027	3.511	0.054	0.767	0.002	1.145	0.000
Sanding done							-0.759	0.118		
Sanding not done										
Salting done							1.049	0.009		
Salting not done							0.000			
Anti Icing done										
Anti Icing not done										
BPR time	0.066	0.117								
Ln(Alpha)			0.568		1.955		-14.767			
Constant	-100.391	0.000							-1.411	0.024
BPR time									0.080	0.133
RSI	88.595	0.000								
Ln(Exposure)	1.738	0.062								
Observations	341		527		300		370		401	
LL(Null)	-175.36		-74.39		-25.31		-148.64		-361.71	
LL(Model)	-160.04		-58.22		-17.48		-109.93		-270.08	
AIC	338.09		126.44		44.96		235.86		554.16	

Table M-6: Summary results of NB model from EBD analysis

Variable	EBD-NB1		EBD-NB2		EBD-NB3		EBD-NB4		EBD-NB5		EBD-NB6		EBD-NB7		EBD-NB8	
	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-7.461	0.000	-7.184	0.000	-6.072	0.000	-6.693	0.000	-5.228	0.000	-5.287	0.000	-3.950	0.000	1.239	0.223
October	0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
November	-0.955	0.000	-0.976	0.000	-1.104	0.000	-1.080	0.000	-1.038	0.000	-1.036	0.000	-1.047	0.000	-1.047	0.000
December	-1.110	0.000	-1.130	0.000	-1.259	0.000	-1.243	0.000	-1.172	0.000	-1.170	0.000	-1.168	0.000	-1.168	0.000
January	-1.028	0.000	-1.048	0.000	-1.196	0.000	-1.181	0.000	-1.092	0.000	-1.088	0.000	-1.110	0.000	-1.110	0.000
February	-1.399	0.000	-1.418	0.000	-1.564	0.000	-1.555	0.000	-1.461	0.000	-1.458	0.000	-1.484	0.000	-1.485	0.000
March	-1.149	0.000	-1.167	0.000	-1.310	0.000	-1.302	0.000	-1.197	0.000	-1.194	0.000	-1.220	0.000	-1.220	0.000
April	-0.875	0.002	-0.891	0.001	-1.036	0.000	-1.035	0.000	-0.949	0.001	-0.947	0.001	-1.019	0.000	-1.019	0.000
Wind Speed	0.009	0.004	0.009	0.006	0.006	0.041	0.007	0.019	0.009	0.006	0.009	0.006	0.009	0.005	0.009	0.005
visibility	-0.032	0.000	-0.032	0.000	-0.038	0.000	-0.039	0.000	-0.031	0.000	-0.031	0.000	-0.041	0.000	-0.041	0.000
RSI	-4.629	0.000	-4.647	0.000	-4.750	0.000	-4.767	0.000	-4.909	0.000	-4.916	0.000	-4.955	0.000	-4.956	0.000
Ln(Exposure)	0.824	0.000			0.759	0.000			0.722	0.000			0.685	0.000		
Traffic Exposure			0.820	0.000			0.745	0.000			0.720	0.000			0.685	0.000
Length Exposure			0.773	0.000			0.983	0.000			0.746	0.000			-0.871	0.000
RDTYPE1									0.000							
RDTYPE2									-1.112	0.000	-1.118	0.000				
RDTYPE3									-0.815	0.000	-0.806	0.000				
RDTYPE4									-0.495	0.000	-0.504	0.000				
RDTYPE5									-0.554	0.000	-0.582	0.000				
RDTYPE6									-1.148	0.000	-1.155	0.000				
RDTYPE7									-1.286	0.000	-1.306	0.000				
RDTYPE8									-0.852	0.000	-0.883	0.000				
Region1							0.000									
Region2					-0.512	0.000	-0.707	0.000								
Region3					-0.362	0.002	-0.514	0.000								
Region4					-0.546	0.001	-0.852	0.000								
Region5					-0.200	0.012	-0.437	0.000								
Sioux Narrows													-2.433	0.000	-0.317	0.521
Elliot Lake													-0.948	0.055	-0.267	0.585
Grand Bend													-2.782	0.000	-1.633	0.000
Carleton													-3.256	0.000	-3.413	0.000
Shabauqua													-2.285	0.000	-1.896	0.000

Table M – 6: Cont.

Variable	EBD-NB1		EBD-NB2		EBD-NB3		EBD-NB4		EBD-NB5		EBD-NB6		EBD-NB7		EBD-NB8	
	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Cochrane													-1.718	0.000	-0.335	0.278
North Bay													-1.298	0.000	-0.365	0.125
Massey													-1.114	0.000	0.070	0.782
Nipigon													-2.056	0.000	0.000	
Port Severn													-1.993	0.000	-0.986	0.000
Graven Hurst													-1.665	0.000	-1.171	0.000
Kenora													-1.274	0.000	0.791	0.012
Kaladar													-1.215	0.000	0.744	0.022
Snelgrove													-2.106	0.000	-2.059	0.000
Simcoe													-1.490	0.000	1.013	0.005
Shelburne													-1.953	0.000	-0.755	0.001
Morrisburg													-1.405	0.000	0.678	0.026
QEW 2													-1.415	0.000	-1.289	0.000
Highway 410													-1.626	0.000	-2.828	0.000
Dunvegan													-1.426	0.000	0.769	0.014
Port Hope													-0.647	0.000	0.954	0.000
Patrol 5													-1.361	0.000	-2.544	0.000
QEW 1													-1.110	0.000	-1.575	0.000
Patrol 4													-0.995	0.000	-1.731	0.000
Kanata Patrol													-1.595	0.000	-1.020	0.000
Woodstock													-0.818	0.000	0.657	0.002
Patrol 1													-1.191	0.000	-0.963	0.000
Hwy 404													-1.665	0.000	-1.217	0.000
Maple													-1.277	0.000	-0.731	0.000
Patrol 3													-0.996	0.000	-0.828	0.000
Patrol 2													0.000		0.000	
Ln(Alpha)	0.213		0.212		0.160		0.158		0.051		0.052		-0.210		-0.210	
Observations	10932		10932		10932		10932		10932		10932		10932		10932	
LL(Null)	-6503.48		-6503.48		-6503.48		-6503.48		-6503.48		-6503.48		-6503.48		-6095.81	
LL(Model)	-5097.46		-5097.4		-5074.99		-5068.3		-5000.39		-5000.84		-4860.68		-4835.02	
AIC	10218.92		10220.79		10181.98		10170.61		10038.79		10041.68		9805.364		9762.045	

Appendix N: HBD – Results for Individual Sites Using PLN

TABLE N – 1: HBD Results for Individual Sites

	Wood Stock		Snelgrove		Sioux Narrows		Simcoe		Shelburne		Shabauqua		QEW2	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-3.189	0.015	-2.298	0.000	-4.901	0.002	-8.831	0.002	-8.666	0.000	-65.770	0.072	-4.755	0.028
Monthly ID														
Air Temperature (C^o)							0.063	0.079	0.143	0.002			-0.044	0.136
Wind Speed (Km/hr)	0.019	0.017							0.028	0.146				
visibility (km)	-0.064	0.000					-0.032	0.130	-0.047	0.087			-0.123	0.000
Precipitation													0.432	0.111
RSI	-3.176	0.000	-4.635	0.000	-5.540	0.002	-3.693	0.000	-4.207	0.000	-19.158	0.000	-2.595	0.000
Ln(Exposure)	0.222	0.060					0.705	0.011	0.669	0.005	8.516	0.069	0.303	0.121
First two hours														
Other hours														
Observations	4982		3856		4183		4764		4871		2674		3315	
LL(Model)	-990.36		-135.86		-38.55		-265.138		-223.33		-15.18		-314.97	
AIC	1992.73		277.71		83.10		542.276		460.66		38.35		643.95	

TABLE N – 2: HBD Results for Individual Sites

	QEW1		Port Severn		Port Hope		Patrol 5		Patrol 4		Patrol 3	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-7.870	0.000	-5.551	0.009	-5.807	0.005	-7.848	0.002	-3.746	0.056	-1.563	0.000
Monthly ID												
Air Temperature (C^o)	-0.052	0.101	0.131	0.010								
Wind Speed (Km/hr)	0.047	0.000										
visibility (km)	-0.027	0.115			-0.020	0.054	-0.081	0.003	-0.046	0.016	-0.031	0.001
Precipitation	-0.666	0.089			0.393	0.024	-1.614	0.034				
RSI	-4.120	0.000	-3.501	0.000	-3.432	0.000	-4.293	0.000	-3.301	0.000	-1.602	0.000
Ln(Exposure)	0.526	0.003	0.359	0.123	0.443	0.013	0.721	0.002	0.282	0.121		
First two hours	0.549	0.107									0.376	0.040
Other hours	0.000											
Observations	3477		4695		2872		2986		2449		3635	
LL(Model)	-410.86		-165.88		-638.72		-225.50		-296.87		-1046.05	
AIC	839.72		341.76		1289.45		462.99		603.75		2102.09	

TABLE N – 3: HBD Results for Individual Sites

	Patrol 2		Patrol 1		North Bay		Nipigon		Morrisburg		Massey	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-2.695	0.002	-4.019	0.002	-8.767	0.002	-12.492	0.007	-0.264	0.419	-3.193	0.000
Monthly ID	-0.081	0.073			-0.340	0.026						
Air Temperature (C^o)	-0.032	0.017					0.099	0.035				
Wind Speed (Km/hr)												
visibility (km)	-0.034	0.000	-0.040	0.000							-0.072	0.018
Precipitation	-0.483	0.006										
RSI	-1.534	0.000	-2.420	0.000	-3.556	0.000	-1.299	0.221	-5.358	0.000	-1.790	0.058
Ln(Exposure)	0.193	0.008	0.201	0.057	0.843	0.011	0.904	0.058				
First two hours			0.444	0.054								
Other hours			0.000									
Observations	4117		3983		5956		2813		2868		3433	
LL(Model)	-1690.71		-744.91		-170.76		-106.47		-250.95		-164.44	
AIC	3397.41		1501.81		351.51		222.95		507.90		336.89	

TABLE N – 4: HBD Results for Individual Sites

	Maple		Kenora		Kanata		Kaladar		Graven Hurst		Grand Bend	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-6.515	0.001	-5.439	0.058	-0.479	0.255	-2.797	0.000	-5.416	0.007	-6.892	0.000
Monthly ID			-0.349	0.007					-0.438	0.001		
Air Temperature (C^o)	-0.043	0.011							0.061	0.052		
Wind Speed (Km/hr)	0.017	0.012	0.043	0.069								
visibility (km)	-0.058	0.000	-0.051	0.067	-0.028	0.069						
Precipitation			-1.611	0.095								
RSI	-0.984	0.000	-3.852	0.000	-3.537	0.000	-3.097	0.001	-3.729	0.000	0.619	0.753
Ln(Exposure)	0.322	0.041	0.441	0.145					0.513	0.012		
First two hours	0.492	0.023			-0.564	0.012						
Other hours	0.000				0.000							
Observations	4532		5154		3548		3559		5272		3860	
LL(Model)	-956.80		-209.79		-443.32		-143.97		-280.19		-44.75	
AIC	1929.60		435.57		896.63		293.94		572.37		95.50	

TABLE N – 5: HBD Results for Individual Sites

	Elliot Lake		Dunvegan		Cochrane		Carleton		410		404	
Variable	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig	B	Sig
Constant	-7.663	0.001	-13.700	0.000	-4.705	0.000	-2.204	0.149	-2.205	0.003	-1.802	0.000
Monthly ID									-0.265	0.033		
Air Temperature (C^o)											-0.065	0.000
Wind Speed (Km/hr)			-0.040	0.028	0.058	0.014						
visibility (km)			-0.032	0.074							-0.042	0.000
Precipitation												
RSI	-1.252	0.601	-4.950	0.000	-4.225	0.000	-8.189	0.001	-1.751	0.006	-1.805	0.000
Ln(Exposure)			1.259	0.000								
First two hours												
Other hours												
Observations	3411		3146		7157		2761		3619		4109	
LL(Model)	-35.95		-310.70		-107.75		-31.44		-260.97		-770.28	
AIC	77.90		633.39		223.50		68.88		529.94		1550.55	

Appendix O: Exploratory Data Analysis Results for Severity Data

Table O – 1: Injury Severity Distribution for Occupant Based Data – AWCD

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Road Type	Freeways	3%	19%	78%
	Multilane Kings	11%	28%	62%
	2 Lane Kings	15%	28%	57%
Day of Week	Weekdays	4%	19%	77%
	Weekends	5%	20%	76%
Light	Light	4%	19%	77%
	Dark	4%	20%	75%
Accident Location	Intersections	4%	21%	75%
	Segment	4%	19%	77%
	Bridges/Underpasses	9%	20%	70%
Speed Limit	< 100 Km/hr	9%	23%	68%
	>= 100 Km/hr	3%	19%	78%
Road Condition	Good	4%	19%	77%
	Poor	4%	26%	70%
Road Alignment	Straight on Level	4%	18%	78%
	Straight on Hill	5%	22%	73%
	Curve on Level	7%	26%	67%
	Curve on Hill	6%	26%	68%
Environment	Otherwise	4%	19%	77%
	Snow/freezing rain	5%	23%	72%
Sex of Driver	Male	4%	18%	78%
	Female	3%	24%	73%
Driver Condition	Otherwise	7%	22%	71%
	Normal	3%	19%	78%
Vehicle Type	SUVs/Car/Station Wagon	4%	21%	76%
	Van	5%	17%	78%
	Large Trucks etc.	6%	13%	81%
Position in vehicle	Front	4%	20%	76%
	Rear	5%	17%	78%
Safety Equipment	Used	3%	19%	78%
	Not or Bad used	14%	28%	58%

Table O – 1: Cont.

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Driver Age	< 25	4%	22%	74%
	25 - 35	3%	18%	79%
	35 - 60	4%	19%	77%
	> 60	6%	22%	72%
Vehicle Age	< 2	4%	18%	78%
	2 - 5	4%	19%	77%
	5 - 7	4%	20%	76%
	7 - 10	3%	20%	77%
	> 10	4%	22%	74%
Traffic Volume	< 1000	12%	28%	60%
	1000 - 2500	4%	21%	75%
	2500 - 5000	3%	20%	77%
	5000 - 7500	2%	17%	81%
	7500 - 10000	2%	15%	83%
	> 10000	1%	14%	85%
Wind Speed	< 10	4%	21%	74%
	10 - 15	4%	19%	77%
	15 - 25	4%	19%	77%
	> 25	4%	19%	77%
Visibility	< 5	6%	22%	73%
	5 - 10	5%	22%	73%
	10 - 15	4%	20%	77%
	> 15	3%	19%	78%
Number of Lanes	< 2	7%	22%	70%
	2 - 4	6%	25%	69%
	4 - 8	3%	22%	75%
	> 8	1%	11%	88%
Road Surface Condition	Wet or Snow etc.	5%	22%	73%
	Dry	3%	18%	79%

Table O – 2: Injury Severity Distribution for Vehicle Based Data – AWCD

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Road Type	Freeways	4%	29%	66%
	Multilane Kings	13%	36%	51%
	2 Lane Kings	18%	38%	44%
Day of Week	Weekdays	5%	30%	65%
	Weekends	6%	30%	64%
Light	Light	5%	30%	65%
	Dark	6%	30%	64%
Accident Location	Intersections	5%	31%	64%
	Segment	5%	30%	65%
	Bridges/Underpasses	11%	31%	57%
Speed Limit	< 100 Km/hr	10%	33%	56%
	>= 100 Km/hr	4%	30%	66%
Road Condition	Good	5%	30%	65%
	Poor	5%	40%	54%
Road Alignment	Straight on Level	5%	29%	67%
	Straight on Hill	7%	35%	58%
	Curve on Level	9%	37%	55%
	Curve on Hill	7%	37%	57%
Environment	Otherwise	5%	29%	66%
	Snow/freezing rain	6%	34%	60%
Sex of Driver	Male	6%	28%	66%
	Female	5%	34%	62%
Driver Condition	Otherwise	9%	33%	58%
	Normal	4%	29%	66%
Vehicle Type	SUVs/Car/Station Wagon	5%	30%	65%
	Van	7%	32%	61%
	Large Trucks etc.	8%	21%	71%
Position in vehicle	Front	5%	30%	65%
	Rear	8%	31%	61%
Safety Equipment	Used	5%	30%	65%
	Not or Bad used	15%	37%	48%
Driver Age	< 25	5%	31%	64%
	25 - 35	5%	29%	67%
	35 - 60	5%	30%	64%
	> 60	8%	32%	60%

Table O – 2: Cont.

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Vehicle Age	< 2	6%	28%	67%
	2 - 5	5%	29%	65%
	5 - 7	5%	32%	63%
	7 - 10	5%	32%	63%
	> 10	6%	31%	64%
Traffic Volume	< 1000	14%	38%	48%
	1000 - 2500	6%	32%	63%
	2500 - 5000	4%	31%	65%
	5000 - 7500	3%	27%	71%
	7500 - 10000	2%	25%	72%
	> 10000	1%	24%	74%
Wind Speed	< 10	6%	32%	62%
	10 - 15	5%	30%	65%
	15 - 25	5%	29%	66%
	> 25	5%	29%	66%
Visibility	< 5	7%	32%	61%
	5 - 10	6%	33%	61%
	10 - 15	5%	29%	66%
	> 15	5%	29%	66%
Number of Lanes	< 2	9%	32%	59%
	2 - 4	8%	37%	55%
	4 - 8	5%	34%	61%
	> 8	1%	18%	81%
Road Surface Condition	Wet or Snow etc.	6%	33%	61%
	Dry	5%	28%	67%

Table O – 3: Injury Severity Distribution for Collision Based Data – AWCD

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Road Type	Freeways	5%	40%	55%
	Multilane Kings	15%	42%	43%
	2 Lane Kings	19%	44%	38%
Day of Week	Weekdays	6%	40%	54%
	Weekends	8%	41%	51%
Light	Light	6%	40%	54%
	Dark	7%	40%	53%
Accident Location	Intersections	7%	41%	52%
	Segment	6%	40%	54%
	Bridges/Underpasses	10%	41%	49%
Speed Limit	< 100 Km/hr	12%	41%	47%
	>= 100 Km/hr	6%	40%	55%
Road Condition	Good	6%	40%	54%
	Poor	7%	53%	41%
Road Alignment	Straight on Level	6%	39%	55%
	Straight on Hill	8%	45%	47%
	Curve on Level	9%	43%	48%
	Curve on Hill	8%	44%	48%
Environment	Otherwise	6%	40%	54%
	Snow/freezing rain	7%	41%	52%
Sex of Driver	Male	8%	40%	52%
	Female	5%	40%	55%
Driver Condition	Otherwise	10%	42%	48%
	Normal	5%	40%	55%
Vehicle Type	SUVs/Car/Station Wagon	5%	40%	55%
	Van	8%	41%	51%
	Large Trucks etc.	14%	46%	40%
Position in vehicle	Front	6%	40%	54%
	Rear	10%	39%	51%
Safety Equipment	Used	6%	40%	54%
	Not or Bad used	19%	50%	31%
Driver Age	< 25	6%	43%	50%
	25 - 35	6%	38%	56%
	35 - 60	7%	40%	53%
	> 60	11%	45%	44%

Table O – 3: Cont.

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Vehicle Age	< 2	7%	40%	53%
	2 - 5	7%	39%	54%
	5 - 7	6%	39%	55%
	7 - 10	6%	41%	53%
	> 10	7%	43%	50%
Traffic Volume	< 1000	14%	44%	42%
	1000 - 2500	7%	42%	51%
	2500 - 5000	5%	41%	53%
	5000 - 7500	4%	37%	59%
	7500 - 10000	3%	37%	60%
	> 10000	2%	37%	62%
Wind Speed	< 10	7%	42%	50%
	10 - 15	6%	40%	54%
	15 - 25	6%	38%	55%
	> 25	6%	40%	54%
Visibility	< 5	7%	41%	53%
	5 - 10	7%	42%	51%
	10 - 15	7%	38%	55%
	> 15	6%	40%	54%
Number of Lanes	< 2	10%	39%	51%
	2 - 4	9%	48%	44%
	4 - 8	6%	46%	48%
	> 8	2%	26%	72%
Road Surface Condition	Wet or Snow etc.	7%	41%	52%
	Dry	6%	39%	54%

Table O – 4: Collision Count by Severity for Occupant Based Data – AWCD

SITE	Minimal Injury +PD only	Minor Injury	Fatality + Major Injury	Total
Sioux Narrows	24	13	6	43
Elliot Lake	24	16	1	41
Grand Bend	29	14	16	59
Carleton	35	9	6	50
Shabauqua	22	13	7	42
Cochrane	59	28	14	101
North Bay	129	65	34	228
Massey	132	63	28	223
Nipigon	137	64	42	243
Port Severn	139	76	53	268
Graven Hurst	178	91	31	300
Kenora	156	80	45	281
Kaladar	195	71	66	332
Snelgrove	219	83	33	335
Simcoe	223	133	43	399
Shelburne	298	136	57	491
Morrisburg	292	164	71	527
QEW 2	400	146	25	571
Highway 410	464	210	33	707
Dunvegan	539	228	116	883
Port Hope	709	292	82	1083
Patrol 5	895	186	33	1114
QEW 1	1145	287	49	1481
Patrol 4	1099	300	36	1435
Kanata	1312	358	59	1729
Woodstock	1185	619	201	2005
Patrol 1	1720	490	63	2273
Hwy 404	2154	446	53	2653
Maple	2114	593	76	2783
Patrol 3	5146	995	102	6243
Patrol 2	9073	1464	104	10641
All Sites	30246	7733	1585	39564

Table O – 5: Collision Count by Severity for Vehicle Based Data – AWCD

SITE	Minimal Injury +PD only	Minor Injury	Fatality + Major Injury	Total
Sioux Narrows	13	11	4	28
Elliot Lake	9	11	1	21
Grand Bend	9	8	10	27
Carleton	13	5	6	24
Shabauqua	9	8	5	22
Cochrane	28	21	11	60
North Bay	52	52	16	120
Massey	52	46	17	115
Nipigon	63	39	23	125
Port Severn	47	54	23	124
Graven Hurst	96	64	19	179
Kenora	53	53	31	137
Kaladar	79	52	39	170
Snelgrove	90	61	22	173
Simcoe	98	97	27	222
Shelburne	120	92	35	247
Morrisburg	109	118	41	268
QEW 2	173	109	20	302
Highway 410	186	160	23	369
Dunvegan	247	177	62	486
Port Hope	291	219	44	554
Patrol 5	390	155	20	565
QEW 1	459	227	34	720
Patrol 4	427	238	35	700
Kanata	548	292	47	887
Woodstock	493	439	128	1060
Patrol 1	706	392	50	1148
Hwy 404	965	351	38	1354
Maple	870	464	49	1383
Patrol 3	2108	789	78	2975
Patrol 2	3895	1101	74	5070
All Sites	12698	5905	1032	19635

Table O – 6: Collision Count by Severity for Collision Based Data – AWCD

SITE	Minimal Injury +PD only	Minor Injury	Fatality + Major Injury	Total
Sioux Narrows	11	11	4	26
Elliot Lake	9	11	1	21
Grand Bend	5	8	7	20
Carleton	8	5	6	19
Shabauqua	5	8	4	17
Cochrane	24	19	10	53
North Bay	31	45	13	89
Massey	39	43	13	95
Nipigon	42	36	18	96
Port Severn	38	53	19	110
Graven Hurst	84	62	18	164
Kenora	38	52	30	120
Kaladar	47	44	33	124
Snelgrove	48	53	19	120
Simcoe	63	87	24	174
Shelburne	66	78	30	174
Morrisburg	91	117	35	243
QEW 2	110	98	19	227
Highway 410	119	152	23	294
Dunvegan	189	171	38	398
Port Hope	210	213	38	461
Patrol 5	216	151	17	384
QEW 1	248	209	26	483
Patrol 4	220	221	35	476
Kanata	306	271	44	621
Woodstock	325	409	100	834
Patrol 1	410	365	47	822
Hwy 404	585	335	36	956
Maple	509	436	45	990
Patrol 3	1112	745	73	1930
Patrol 2	2141	1023	70	3234
All Sites	7349	5531	895	13775

Table O – 7: Injury Severity Distribution for Occupant Based Data – SECD

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Road Type	Freeways	4%	21%	75%
	Multilane Kings	9%	28%	63%
	2 Lane Kings	18%	28%	55%
Day of Week	Weekdays	5%	22%	72%
	Weekends	4%	21%	75%
Light	Light	6%	21%	73%
	Dark	4%	23%	73%
Accident Location	Intersections	3%	21%	76%
	Segment	5%	22%	73%
	Bridges/Underpasses	16%	24%	60%
Speed Limit	< 100 Km/hr	12%	24%	64%
	>= 100 Km/hr	4%	21%	75%
Road Condition	Good	5%	21%	73%
	Poor	2%	29%	69%
Road Alignment	Straight on Level	4%	21%	74%
	Straight on Hill	7%	23%	71%
	Curve on Level	10%	23%	67%
	Curve on Hill	6%	25%	69%
Environment	Otherwise	6%	21%	74%
	Snow/freezing rain	5%	22%	73%
Sex of Driver	Male	5%	20%	75%
	Female	5%	26%	69%
Driver Condition	Otherwise	6%	24%	71%
	Normal	5%	21%	74%
Vehicle Type	SUVs/Car/Station Wagon	4%	23%	73%
	Van	6%	21%	73%
	Large Trucks etc.	7%	14%	78%
Position in vehicle	Front	5%	22%	73%
	Rear	6%	20%	75%
Safety Equipment	Used	5%	21%	75%
	Not or Bad used	13%	33%	54%
Driver Age	< 25	5%	24%	72%
	25 - 35	4%	21%	75%
	35 - 60	5%	21%	74%
	> 60	9%	25%	66%

Table O – 7: Cont.

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Vehicle Age	< 2	5%	21%	73%
	2 - 5	5%	22%	73%
	5 - 7	5%	21%	74%
	7 - 10	4%	23%	73%
	> 10	5%	21%	73%
Traffic Volume	< 1000	11%	28%	61%
	1000 - 2500	5%	21%	74%
	2500 - 5000	3%	20%	77%
	5000 - 7500	2%	20%	78%
	7500 - 10000	3%	15%	82%
	> 10000	1%	18%	81%
Wind Speed	< 10	4%	22%	74%
	10 - 15	5%	23%	72%
	15 - 25	6%	21%	73%
	> 25	4%	21%	75%
Visibility	< 5	5%	22%	73%
	5 - 10	9%	22%	69%
	10 - 15	4%	19%	77%
	> 15	4%	22%	74%
Number of Lanes	< 2	9%	23%	68%
	2 - 4	8%	26%	66%
	4 - 8	3%	23%	73%
	> 8	1%	13%	86%
Road Surface Condition	Wet or Snow etc.	5%	22%	72%
	Dry	4%	17%	79%

Table O – 8: Injury Severity Distribution for Vehicle Based Data – SECD

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Road Type	Freeways	5%	32%	63%
	Multilane Kings	11%	39%	50%
	2 Lane Kings	17%	39%	44%
Day of Week	Weekdays	6%	33%	60%
	Weekends	6%	32%	62%
Light	Light	7%	32%	61%
	Dark	6%	33%	61%
Accident Location	Intersections	5%	31%	65%
	Segment	6%	33%	61%
	Bridges/Underpasses	18%	36%	45%
Speed Limit	< 100 Km/hr	13%	34%	53%
	>= 100 Km/hr	5%	32%	63%
Road Condition	Good	6%	32%	62%
	Poor	3%	48%	48%
Road Alignment	Straight on Level	5%	32%	63%
	Straight on Hill	8%	36%	56%
	Curve on Level	11%	36%	53%
	Curve on Hill	8%	32%	60%
Environment	Otherwise	7%	31%	62%
	Snow/freezing rain	6%	34%	61%
Sex of Driver	Male	7%	31%	63%
	Female	5%	36%	58%
Driver Condition	Otherwise	8%	33%	59%
	Normal	6%	33%	62%
Vehicle Type	SUVs/Car/Station Wagon	5%	32%	62%
	Van	9%	35%	56%
	Large Trucks etc.	7%	24%	69%
Position in vehicle	Front	6%	32%	62%
	Rear	9%	36%	55%
Safety Equipment	Used	6%	32%	62%
	Not or Bad used	13%	43%	44%
Driver Age	< 25	4%	34%	62%
	25 - 35	6%	32%	63%
	35 - 60	7%	33%	61%
	> 60	11%	34%	54%

Table O – 8: Cont.

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Vehicle Age	< 2	6%	31%	62%
	2 - 5	7%	34%	60%
	5 - 7	6%	32%	63%
	7 - 10	6%	35%	59%
	> 10	6%	31%	63%
Traffic Volume	< 1000	12%	39%	49%
	1000 - 2500	6%	33%	61%
	2500 - 5000	4%	31%	66%
	5000 - 7500	3%	31%	66%
	7500 - 10000	4%	24%	72%
	> 10000	2%	30%	69%
Wind Speed	< 10	5%	33%	61%
	10 - 15	6%	34%	60%
	15 - 25	7%	32%	61%
	> 25	5%	33%	62%
Visibility	< 5	5%	33%	62%
	5 - 10	11%	34%	56%
	10 - 15	6%	28%	66%
	> 15	5%	33%	61%
Number of Lanes	< 2	10%	31%	59%
	2 - 4	10%	40%	51%
	4 - 8	4%	36%	59%
	> 8	1%	21%	78%
Road Surface Condition	Wet or Snow etc.	6%	34%	60%
	Dry	6%	26%	68%

Table O – 9: Injury Severity Distribution for Collision Based Data – SECD

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Road Type	Freeways	6%	41%	53%
	Multilane Kings	13%	41%	46%
	2 Lane Kings	18%	43%	39%
Day of Week	Weekdays	7%	41%	52%
	Weekends	6%	42%	52%
Light	Light	7%	41%	52%
	Dark	6%	42%	52%
Accident Location	Intersections	6%	42%	51%
	Segment	7%	41%	52%
	Bridges/Underpasses	11%	51%	38%
Speed Limit	< 100 Km/hr	14%	40%	45%
	>= 100 Km/hr	5%	42%	53%
Road Condition	Good	7%	40%	53%
	Poor	4%	64%	33%
Road Alignment	Straight on Level	6%	41%	53%
	Straight on Hill	9%	44%	47%
	Curve on Level	9%	43%	47%
	Curve on Hill	10%	36%	54%
Environment	Otherwise	8%	41%	51%
	Snow/freezing rain	6%	42%	52%
Sex of Driver	Male	8%	41%	51%
	Female	6%	42%	53%
Driver Condition	Otherwise	11%	41%	49%
	Normal	6%	41%	53%
Vehicle Type	SUVs/Car/Station Wagon	5%	41%	54%
	Van	10%	42%	49%
	Large Trucks etc.	10%	49%	41%
Position in vehicle	Front	6%	41%	53%
	Rear	10%	44%	46%
Safety Equipment	Used	7%	41%	53%
	Not or Bad used	12%	55%	33%
Driver Age	< 25	4%	43%	53%
	25 - 35	6%	41%	54%
	35 - 60	7%	41%	51%
	> 60	14%	41%	45%

Table O – 9: Cont.

Variable	Categories	Fatality + Major Injury	Minor Injury	Minimal Injury + PD only
Vehicle Age	< 2	6%	41%	53%
	2 - 5	8%	42%	50%
	5 - 7	7%	39%	54%
	7 - 10	6%	41%	53%
	> 10	6%	43%	51%
Traffic Volume	< 1000	13%	44%	43%
	1000 - 2500	7%	42%	51%
	2500 - 5000	5%	40%	56%
	5000 - 7500	3%	40%	57%
	7500 - 10000	3%	36%	61%
	> 10000	2%	42%	55%
Wind Speed	< 10	6%	40%	54%
	10 - 15	7%	45%	49%
	15 - 25	7%	40%	53%
	> 25	7%	42%	51%
Visibility	< 5	5%	41%	54%
	5 - 10	9%	42%	48%
	10 - 15	8%	36%	56%
	> 15	7%	44%	49%
Number of Lanes	< 2	11%	36%	52%
	2 - 4	10%	48%	42%
	4 - 8	5%	48%	47%
	> 8	2%	28%	70%
Road Surface Condition	Wet or Snow etc.	7%	42%	52%
	Dry	9%	37%	54%